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AFWAL-TR-82-2058

TURBINE ENGINE FAULT DETECTION AND ISOLATION PROGRAM
VOLUME I - Turbine Engine Performance Estimation Methods

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1801 Page Mill Road
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AUGUST 1982

FINAL REPORT FOR PERIOD 15 AUGUST 1979 - 30 NOVEMBER 1981

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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER AFWAL-TR-82-2058, Volume I	2. GOVT ACCESSION NO. AD-A119998	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) TURBINE ENGINE FAULT DETECTION AND ISOLATION PROGRAM : Turbine Engine Performance Estimation Methods		5. TYPE OF REPORT & PERIOD COVERED FINAL REPORT August 1979 - November 1981
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Ms. Carolyn Smith, Mr. Mark Broadie, Dr. Ronald DeHoff		8. CONTRACT OR GRANT NUMBER(s) F33615-78-C-2062
9. PERFORMING ORGANIZATION NAME AND ADDRESS SYSTEMS CONTROL TECHNOLOGY, INC. 1801 Page Mill Road Palo Alto, CA 94303		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 30661327
11. CONTROLLING OFFICE NAME AND ADDRESS AERO PROPULSION LABORATORY (AFWAL/POTC) Air Force Wright Aeronautical Laboratories Wright-Patterson AFB, OH 45433		12. REPORT DATE August 1982
		13. NUMBER OF PAGES 240
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) UNCLASSIFIED
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

This report consists of two volumes: Volume II - Maintenance Model Development Report

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

IECMS, TEMS, EDS, MIMS, ECM, TEFDI, TF34, TF41, F100

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This report documents work done for the Turbine Engine Fault Detection and Isolation Program. A gas path performance algorithm has been developed which can be used to trend engine module health. The Maintenance Information Management System was developed for the integration of data into the maintenance framework of the services. These tools have been applied to test data from the F100/EDS, TF34/TEMS and TF41/IECMS data acquisition systems

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I. EXECUTIVE SUMMARY

1.1 INTRODUCTION

High performance aircraft used in modern military service are complex in design, operate under severe levels of stress and temperature, and undergo frequent operational cycles. Consequently, identification of component degradations and failures is difficult. Additionally, inflation and the high cost of engines and spare parts has brought considerable pressure upon the services to search for effective ways to maintain and manage these high-performance propulsion systems. Maintenance based upon monitoring engine condition rather than at specific predetermined intervals has become the ultimate goal.

As a means to attaining this goal, a number of turbine engine monitoring systems have been and are now being developed and tested for possible adaptations to in-service aircraft. What has been lacking in these programs is a means by which this automated data can be integrated into the framework of the Air Force maintenance management organization. Activities of the Turbine Engine Fault Detection and Isolation Program attempt to address this problem. The goal of the program is the development of a data processing procedure which is sensitive to the attributes of flight-acquired engine data and produces output which can be used by maintenance personnel to support the propulsion plant.

This report documents the results of a three-phase program which sequentially presents solutions to several issues associated with the use of performance estimation and automated data acquisition systems within an integrated engine monitoring program. The key questions are:

(1) Can engine performance ratings derived from automated data be integrated into the Air Force maintenance/ logistics organization and interface with existing multi-echelon information systems supporting engine management?

(2) Can a performance estimation algorithm be developed to accurately process automated data to satisfy fault detection, isolation and trending requirements?

(3) Can an integrated engine monitoring system, supported by automatically acquired data, support operational maintenance requirements

Ultimately, solutions to these problems will provide a promising foundation for successful integration of modern data processing and management methods into the diagnostic and maintenance operations for the modern armed services.

1.2 SUMMARY

This report is organized as follows:

- Chapter II: Introduction to Engine Performance Monitoring

This chapter reviews the fundamental aspects of the engine performance monitoring problem. Existing approaches to monitoring and gas path analysis are discussed. Practical aspects of implementing a problem solution are presented as design drivers for the chosen theoretical algorithm.

- Chapter III: Mathematical Methods of Thermodynamic Cycle Monitoring

The evolution of a generic methodology that is applicable over a wide class of engine instrumentation and hardware configurations is presented. In this chapter, the general problem is formulated and the thermodynamic cycle monitoring algorithm is developed.

- Chapter IV: Integration With Maintenance Management

This chapter presents the results of Phase 1, during which requirements for the integration of performance monitoring into the Air Force engine management process were formulated. The Air Force engine management organization is described and the reliability centered maintenance philosophy is discussed. Functional requirements are outlined and keyed to specific software specifications.

- Chapter V: <u>Application to A10/TF34 TEMS Flight Service Evaluation Data</u>

Chapter V examines the concept of an integrated engine monitoring system within the framework of the A10/TF34 TEMS flight service evaluation. Test background is presented along with developments corresponding to the implementation of the thermodynamic cycle monitoring algorithm. Results are highlighted and potential impacts of the system are presented.

- Chapter VI: <u>Application to F15/F100 EDS Flight Test Data</u>

Chapter VI discusses the experiences of the F15/F100 EDS flight test data evaluation. Focus is on the improvement of data acquisition and processing methods which are employed prior to analysis in the thermodynamic cycle monitoring algorithm.

- Chapter VII: <u>Application to A7/TF41 IECMS Deployment</u>

Chapter VII discusses application of the principles of thermodynamic cycle monitoring to IECMS deployment data. Test background, data analysis, and results are presented.

- Chapter VIII: <u>Conclusions</u>

This chapter summarizes the conclusions of the TEFDI program activities. Impacts achievable with the development and implementation of an integrated engine monitoring capability are identified. Based on the conclusions of [illegible] program, recommendations are made for areas which deserve further investigation.

II. TURBINE ENGINE PERFORMANCE MONITORING

Determination of engine health indices is the goal of performance monitoring. Health indices (see Table 2.1) include operating time, vibration, oil contaiment level, particulate size distribution, fatigue cycles, time at temperature, life usage factors, thermodynamic efficiency, and performance. An effective monitoring procedure allows the user systematically to examine, plot, trend, and analyze indices both singly and in conjunction with others. A system which supports comprehensive engine monitoring within a tactical environment (see Figure 2.1) is the goal of the TEFDI program. This chapter reviews the fundamental aspects of the problem and discusses the framework for system design.

2.1 INTRODUCTION

Engine monitoring schemes have been devised to process recorded operating parameters and diagnose engine failures at the flight line. Additional processing is required to track engine deterioration and aging. After many years of feasibility testing and hardware development, the Air Force is installing on-board monitoring on a portion of the tactical inventory [1]. The data utilization scenario often used for this type of hardware is represented in Figure 2.2 [2]. Manufacturer-defined limits and exception criteria are used to trim and troubleshoot the engine. Normal operating data are passed to a central data bank for processing. Advanced monitoring procedures can provide a timely capability to integrate performance and usage data for display and utilization by management personnel.

Before the attributes of several health monitoring approaches are considered, the spectrum of engine symptoms and diagnoses will be examined. Table 2.2 lists a representative sample of engine faults, and procedures useful for detecting them. On-board data systems typically check parameter exceedances and indicate ground inspection activity. More sophisticated modeling and processing of accumulated data can produce subtle inferences

Table 2.1

Engine Health Indices

<u>LOW CYCLE FATIGUE (LCF)</u>

CUMULATIVELY INDUCED PLASTIC STRAIN DAMAGES

LCF EVENT COUNTER IMPLEMENTATION

USAGE FIGURES REPRESENT POPULATION-AVERAGED RESULTS RATHER THAN ENGINE-PARTICULAR

<u>SPECTROGRAPHIC OIL ANALYSIS (SOAP)</u>

ANALYSIS OF ENGINE WEAR PRODUCTS

DETECTION OF NORMAL WEAR CONTENT

COMPLEXITY/TURNAROUND DELAY ARE PROBLEMS

<u>EVENT/EXCEEDANCE DETECTION</u>

COMPATIBLE WITH REAL-TIME DIAGNOSTICS

EXCELLENT FOR TROUBLESHOOTING HARD FAILURES

DOES NOT PRODUCE PROGNOSTICATIVE INFORMATION

<u>ENGINE PERFORMANCE MONITORING</u>

PRODUCES ENGINE PERFORMANCE "STATE"

TRENDING AND PROGNOSTICATION ARE FEASIBLE

OFF-LINE APPROACH

ACCURACY AND RELIABILITY TO BE ESTABLISHED

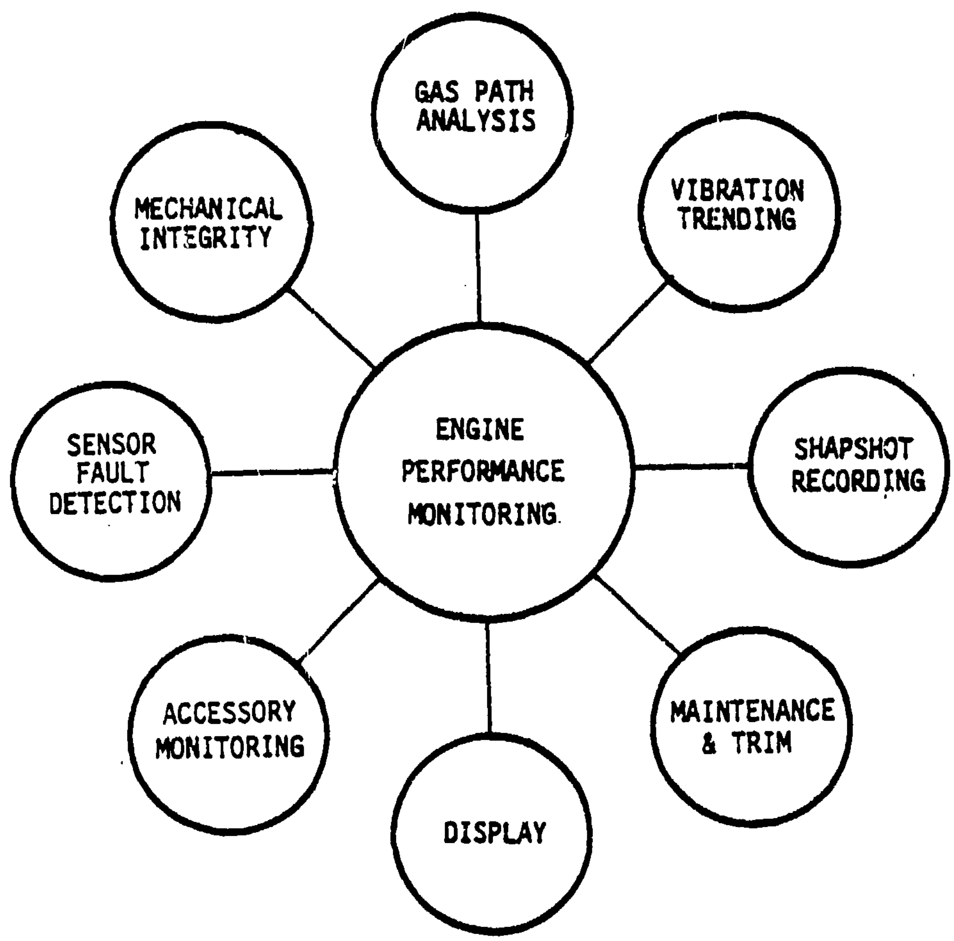


Figure 2.1 Comprehensive Performance Monitoring Aspects

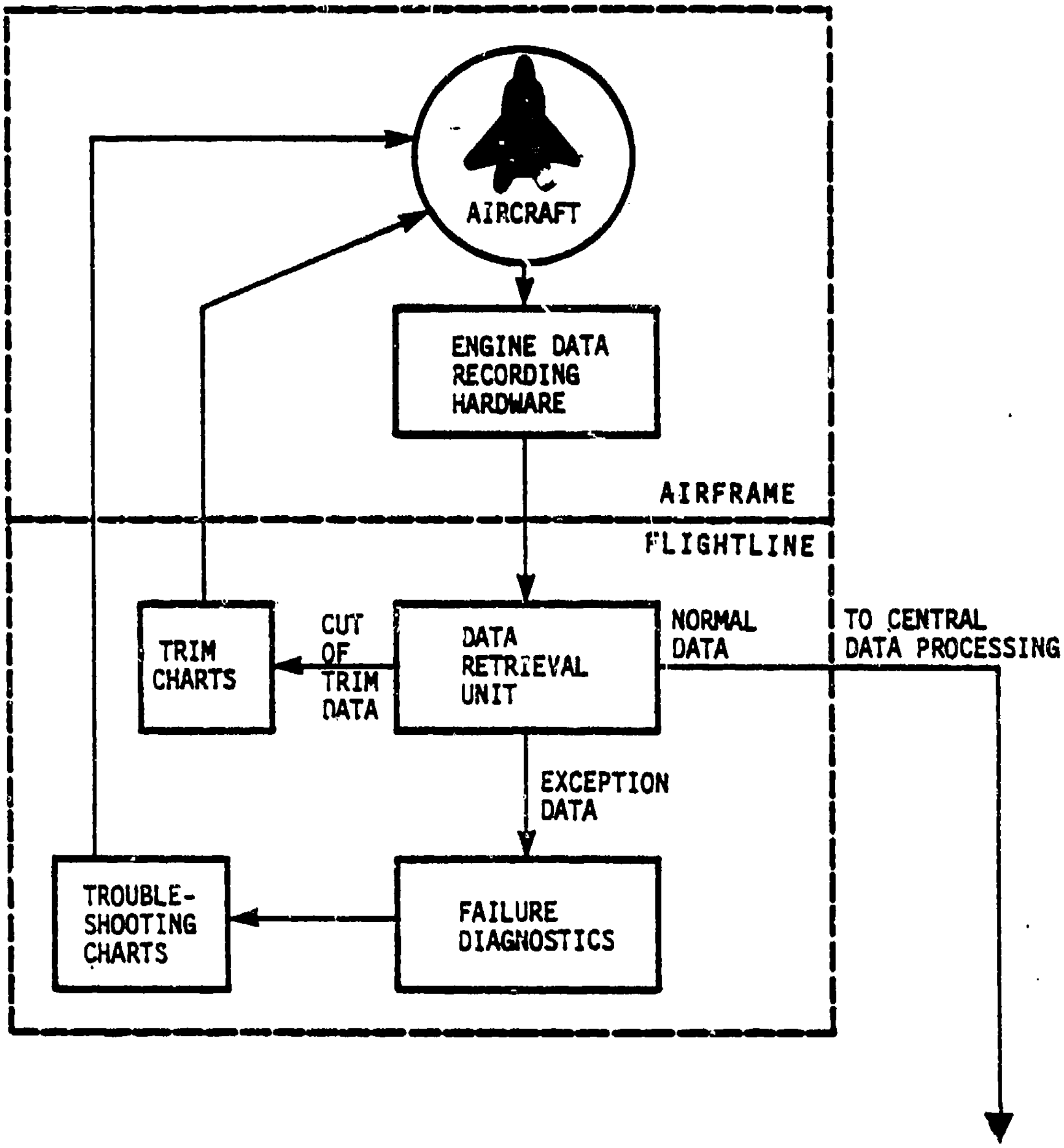


Figure 2.2 Engine Diagnostic View of Data Processing Scenario

Table 2.2

Engine Problems and Diagnostics

PROBLEM	PROBLEM DETECTION PROCEDURE			
	ON-BOARD MONITORING	GROUND INSPECTION	TRENDING & FORECAST	CENTRAL DATA PROCESSING
SECOND STAGE TURBINE BLADE FAILURE	X	X		
THIRD STAGE TURBINE SEAL LEAKAGE	X		X	
FUEL NOZZLE CLOG	X	X	X	
FOREIGN OBJECT DAMAGE	X	X	X	
NO. 4 BEARING FAILURE	X			
TT25 SENSOR OUT	X	X	X	
CONTROL TRIM OUT-OF-BAND			X	
GEOMETRY ACTUATOR FAILURE	X		X	
LOW TURBINE DETERIORATION OUT OF SPEC			X	X
IMPROVED COMBUSTOR LINING DESIGN				X
CONSISTENT TURBINE AREA BUILD DIFFERENCE				X
ENGINE BUILD LINKED TO SUDDEN BLADE FAILURE				X

concerning engine condition. Central data processing can examine and aggregate trend data from many engines.

Until recently, commercial airline approaches to performance analysis have concentrated on manual recording and plotting methods. Uninstalled monitoring methods popular with engine manufacturers differ from the installed approach which has been used by airframe manufacturers and operators. Table 2.3 lists the attributes of the manual system. The uninstalled method (Figure 2.3) examines operating line shifts due to deterioration and the effect of control and trim actions to counteract this effect. In the installed approach, deviations from a point (e.g., take-off power or stabilized cruise) are recorded and trended against owner's manual levels or previous baselines. Both of these approaches do not yield direct information concerning component health levels.

There is a distinct difference between the requirements and capabilities of a <u>diagnostic</u> system and a <u>trending analysis</u> system. Trending and diagnostic system attributes are compared in Table 2.4.

Engine diagnostic systems use in-flight or flight-line- acquired measurements to determine discrete failure events in the installed engine. The Air Force and Navy are currently evaluating such on-board systems. Trending analysis systems process data recorded by engine monitoring systems to determine the deterioration states of the engine. Deterioration is defined as a slow degradation of performance due to a variety of microscopic effects. Trending analysis has the potential for extracting a large amount of engine performance information from data which would otherwise be discarded. Efficient processing of these data (see Figure 2.4) can produce beneficial maintenance indicators and when integrated with current usage factors (e.g., cycle counts, hot time, and oil analysis), can improve logistics practices as part of a comprehensive engine management system.

Analysis of current engine monitoring techniques and the capability of demonstrated data acquisition hardware lead to a number of significant conclusions [3] concerning the development and integration of an automated diagnostic procedure. Some of these are summarized below (also, see Refs. 4 through 6).

Table 2.3

Traditional Monitoring Methods

ROUTINELY RECORD AND ANALYZE STABILIZED IN-FLIGHT DATA

COMPARE PERFORMANCE OF INDIVIDUAL ENGINES TO OPERATIONS MANUAL OR TO THE REST OF THE FLEET

PLOT RESULTS VERSUS TIME OR PERCENT OF DESIGN THRUST

TYPICALLY 10 POINTS PER MONTH PER ENGINE

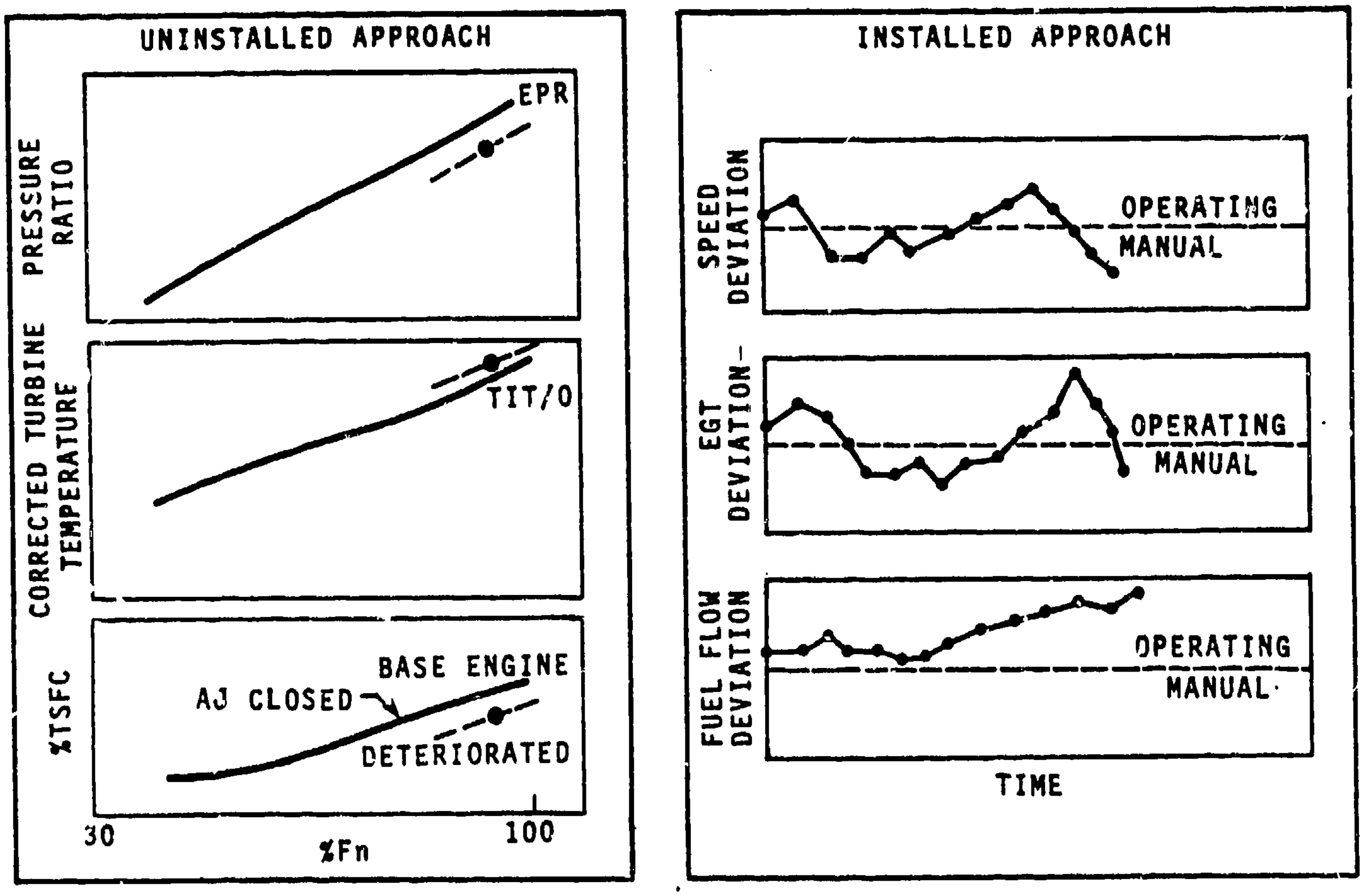


Figure 2.3 Comparison of Two Approaches to Classical Performance Analysis

Table 2.4

Comparison of Trend Analysis and Diagnostics

ENGINE DIAGNOSTICS	TREND ANALYSIS
REAL-TIME PROCESSING	OFF-LINE PROCESSING
IN-FLIGHT/FLIGHTLINE/CALL	BASE/DEPOT LEVEL
DISCRETE EVENTS	CONTINUOUS PARAMETER CHANGES
DISCRETE OUTPUTS	STATISTICAL OUTPUTS
USES PRIMARILY EXCEPTION RECORDING/ EXCEEDANCES	PROCESSES ALL DATA AND EXTRACTS INFORMATION
MICROPROCESSOR	MINI/MACRO COMPUTER
ISOLATES PARTICULAR FAILURE MODES, E.G., SEAL FAILURE	GIVES MODULE-DIRECTED DETERIOR-ATION INFORMATION
SENSOR FAILURE ISOLATION	SENSOR FAILURE ISOLATION
PERFORMANCE WITHIN BOUNDS CHECKING	ACCURATE PERFORMANCE SHIFT CALCULATION

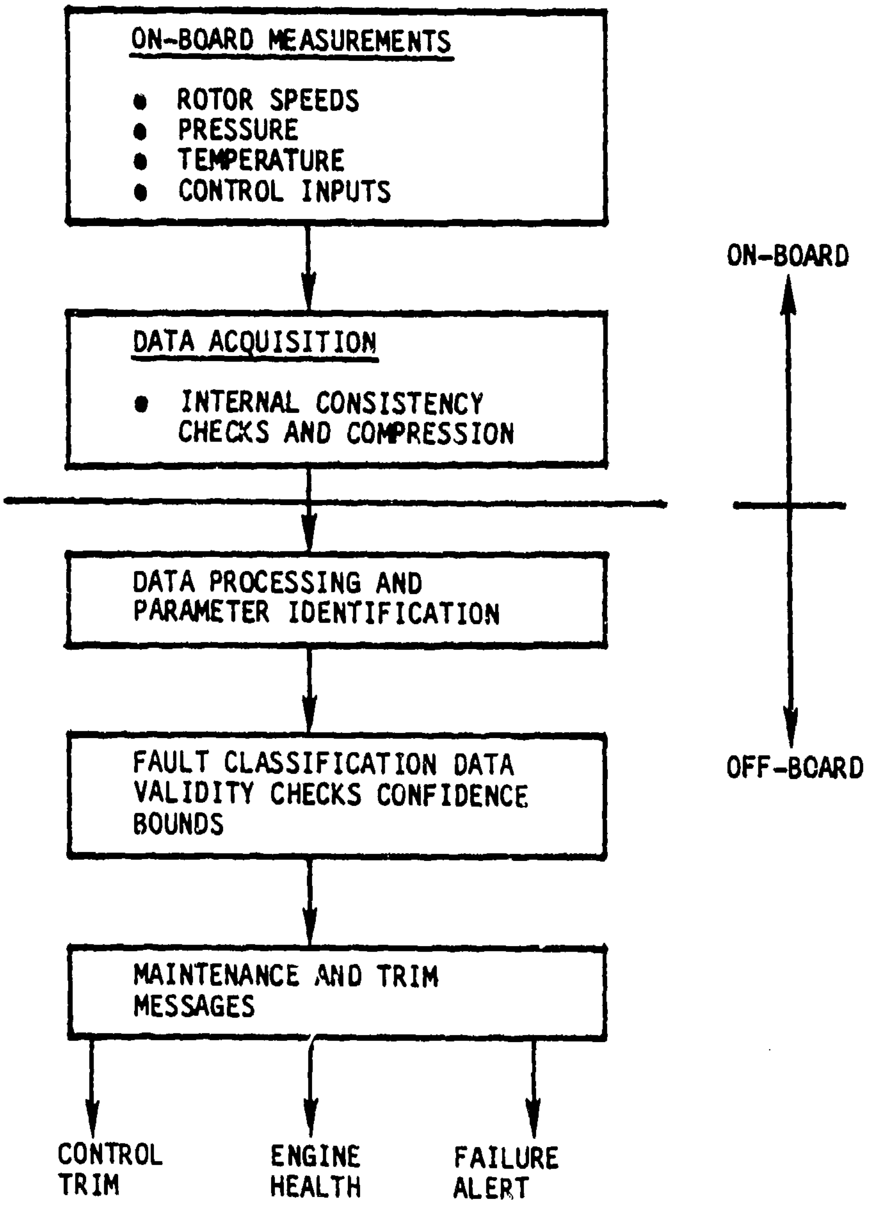


Figure 2.4 Processing Flow for Engine Performance Diagnostics Using Automated TEMS

(1) Integration of the most used engine usage factors, e.g., total operating time, low-cycle fatigue (LCF) counts, and oil analysis into operation is primarily a data management and display problem [7].

(2) Gas path analysis and performance trending have been initially demonstrated in a diagnostic or fault detection mode. The technique is not now used at the base or depot level. This is due primarily to the difficulty in formulating outputs in an easily interpretable format.

(3) Gas path analysis can be integrated into maintenance operations in a consistent manner with other usage factors [1].

2.2 THE THERMODYNAMIC PERFORMANCE MONITORING PROBLEM

Engine performance monitoring can be conceptualized as a three-stage procedure. First, engine operating variables such as rotor speed, pressure, and temperature are recorded. Then, values are compared with operating point variations (e.g., power level and ambient conditions) and variations caused by engine deterioration or failure. Finally, these comparisons are used to infer probable causative agents. Two approaches which will be discussed below are shown in Table 2.5. A complete engine health monitoring methodology must consider each stage relative to the accuracy and suitability of the final result.

2.2.1 Data Acquisition Requirements

The general effectiveness of a condition monitoring system is greatly influenced by the type, frequency, accuracy, and repeatability of the measurements. Instrumentation configuration and data acquisition design are critical elements in reducing the error magnitude. The design methodology must account for sensor errors and further, quantify potential improvements in overall accuracy associated with improved sensor error characteristics. System modeling must consider errors associated with quantization, bias drift, flow distortion, engine thermal disequilibrium, hysteresis, and unsteady operation. Also, data sample rate must be critically evaluated against accuracy improvement and storage requirements. Data collection windows and

Table 2.5

Engine Performance Monitoring Approaches

APPROACH I:	<u>MEASUREMENT TRACKING</u>	
	PARAMETERS ARE MEASURED	
	"MODELS" ARE GEOMETRIC CORRECTIONS	
	BASELINE IS ACCEPTANCE STANDARD AT SINGLE POINT	
APPROACH II:	<u>PERFORMANCE INFERENCE</u>	
	PARAMETERS ARE CALCULATED	
	MODEL IS ANALYTIC	
	BASELINE IS CUSTOM OR GENERIC "OPERATING LINE"	

Table 2.6

Trade-offs In Instrumentation and Data Acquisition System Design

SYSTEM COMPONENT			TRADE-OFFS
SENSORS	ACCURACY NUMBER PLACEMENT	vs.	COST RELIABILITY WEIGHT MAINTAINABILITY POWER CONSUMPTION
SAMPLER (MULTIPLEX)	SAMPLING RATE CHANNEL ERRORS PREFILTERING LOCATION	vs.	COMPLEXITY WEIGHT RELIABILITY POWER CONSUMPTION
RECORDER (ON-BOARD PROCESSOR)	DATA WINDOWS PROCESSING ALGORITHMS STORAGE MEDIUM	vs.	COMPLEXITY/RELIABILITY POWER CONSUMPTION WEIGHT LOCATION/ACCESS
DATA TRANSFER MEDIUM	VOLUME OF DATA CAPACITY SPEED FLIGHT LINE AVAILABILITY	vs.	OPERATIONAL ACCEPTANCE MAINTENANCE INTEGRATION

diagnostic testing procedures should be analyzed relative to overall accuracy improvement and the probability of operational acceptance. Table 2.6 lists important elements in the trade-off analysis of data acquisition and engine instrumentation systems.

2.2.2 Engine Modeling Approaches

The measured parameters must be referenced to "normal" engine operation. The engine model is an analytical tool for associating operating conditions with measured variables. There are several classes of models. The simplest is a display of the operating line referenced to standard conditions [3,8]. Corrected variables are plotted at different points versus one another. These data can be obtained from measurements on a new engine or from thermodynamic equations [8].

Models developed experimentally for a particular engine are termed custom models. Those determined analytically for a nominal or representative engine are called generic models. Deviations of actual engine response from model response are calculated as the distance between measured and modeled points from the custom or generic model as shown in Figure 2.5. The magnitude of these deviations is frequently compared against limits. Exceedance of the limit is interpreted as a fault, as is now discussed.

A class of generic models can be formed. Rather than a display of the output versus a single abscissa variable, an analytical function can be associated with the output and many abscissa variables. This concept is formalized in Chapter III.

The models described above represent normal operation and are termed baseline models. As the engine components deteriorate or age, their effect on the thermodynamic cycle shifts slightly. The microscopic phenomenon (e.g., Table 2.7) which cause aging are of great interest to engine manufacturers and aircraft operators who design and maintain the engines [9,10]. A component model at the phenomenological level is illustrated in Figure 2.6.

It is not practically possible to calculate the extent of each microscopic effect using typical operating data [9]. The laws of thermodynamics can be used within a component level control volume to model

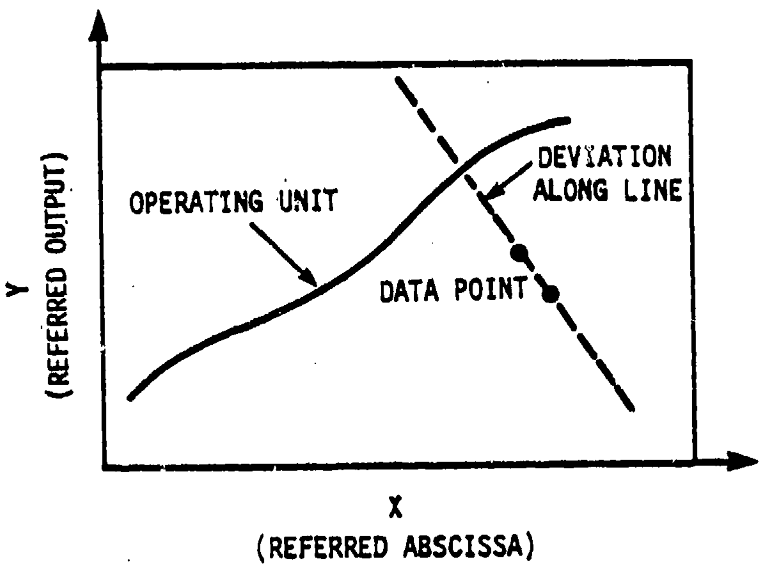


Figure 2.5 Corrected Baseline Model

Table 2.7

Fault Parameter Modeling

MICROSCOPIC EFFECTS BLADE ROUGHNESS BLADE FLOW AREA SEAL WEAR CHOKED NOZZLES AIRFLOW CONTOUR TIP CLEARANCE TRAILING EDGE BLOCKAGE NONUNIFORM FUEL DISTRIBUTION BLADE EROSION FOREIGN OBJECT DAMAGE
MACROSCOPIC EFFECTS EFFICIENCY (NONISENTROPY) AREA (WORK BALANCE) BLEED FLOW (MASS CONSERVATION)
COMBINED TERMS MODULE STATUS (e.g. α_1 (eff) α_2 (area)) TEMPERATURE MARGIN

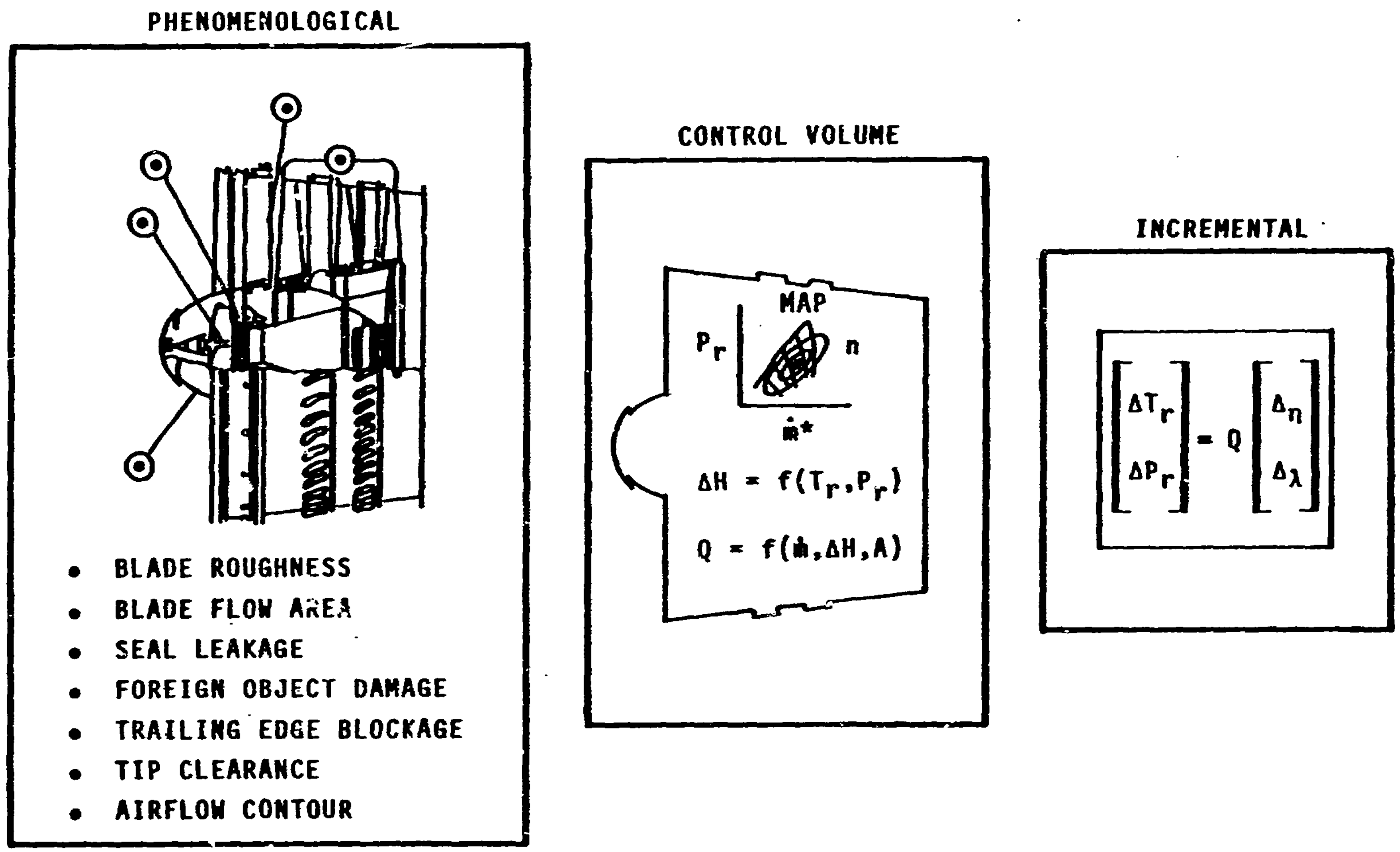


Figure 2.6 Levels of Modeling Detail

Table 2.8

Example of Direct Comparison Method For The CF-6 Engine In Stabilized Cruise

COCKPIT INSTRUMENTS				DERIVED PARAMETERS				
N_2	EGT	EPR	FF	P_3/P_{2C}	T_3/T_{2C}	$P_3/P_{5.4}$	$T_{5.4}/T_3$	POSSIBLE CAUSE
+	+	+	+	+	+	+	+	N_1 INDICATOR MALFUNCTION
+	+	+	+	+	+	NC	NC	DETERIORATION IN LPT
NC	NC	NC	+	NC	NC	NC	NC	FUEL FLOW INDICATOR MALFUNCTION
+	NC	NC	NC	NC	NC	NC	NC	N_2 INDICATOR MALFUNCTION OR VSV's MISRIGGED IN THE CLOSED CONDITION
+	NC	NC	NC	NC	NC	NC	NC	N_2 INDICATOR MALFUNCTION OR VSV's MISRIGGED IN THE OPEN CONDITION
+	+	-	+	- or NC	- or NC	+ or NC	+	EXCESSIVE BLEED CONDITION: COULD BE BLEED DUCT OR MANIFOLD RUPTURE
-	+	-	+	-	+	- or NC	+	COMPRESSOR
+	+	-	-	+	+	+	+	VSV MISRIGGED IN OPEN POSITION
+ or NC	- or NC	-	-	-	-	- or NC	- or NC	FAN DETERIORATION
-	+	+ or NC	-	-	-	NC	+	HPT DETERIORATION

CODE

+ = INCREASING

- = DECREASING

NC = NO CHANGE

(a) DEVIATION: $\Delta y_j = y_j - f_j(u)$

MEASUREMENT CORRECTED TO STANDARD CONDITIONS (p x 1)

CUSTOM OR GENERIC BASELINE

"ABSCISSA" VARIABLE

(b) FAULT COEFFICIENT MODEL

$$\Delta y = H\theta + v$$

FAULT COEFFICIENT MATRIX

FAULT PARAMETERS (q x 1)

MEASUREMENT NOISE

$H = \frac{\partial f}{\partial \theta}$ u = CONSTANT (GENERATED BY SIMULATION OR EMPIRICALLY)

(c) MODEL INVERSION (WEIGHTED LEAST SQUARES)

$$\hat{\Delta\theta} = (H^T R^{-1} H)^{-1} H^T R^{-1} \Delta y$$

Figure 2.7 Linear Performance Analysis

Table 2.9

Linear Performance Analysis

DEMONSTRATED IN TEST CELL RUNS ON COMMERCIAL ENGINES
FAULT COEFFICIENT MATRIX MUST BE MAPPED OVER FLIGHT ENVELOPE REPRESENTING M_N, R_N, ... EFFECTS
BASELINES DEPENDENT ON CONTROL FUNCTION IN MULTIVARIABLE ENGINE
INSTRUMENT ERRORS MUST BE ACCOMMODATED
NUMBER OF MEASUREMENTS > NUMBER OF PARAMETERS
DISTURBANCES RESULT IN BIASED ANSWERS
ERRORS IN MEASURING ABSCISSA VARIABLE BIAS RESULTS
WHITE NOISE EFFECTS CAN BE LESSENED BY AVERAGING
DISTURBANCES (e.g., CUSTOMER BLEEDS) CAN BE APPROXIMATELY ACCOUNTED FOR FROM PERIPHERAL MEASUREMENTS OR SCHEDULES
SENSOR ERRORS CAN BE DETECTED BY DETECTING LARGE DEVIATIONS

Table 2.10

Snapshot Analysis

BASED ON LINEAR POINT DERIVATIVES OF PERFORMANCE

SINGLE SET OF MEASUREMENTS USED

NOISE IN SENSED SIGNALS IMPORTANT

TYPICALLY USED FOR TEST STAND DATA

Table 2.11

Practical Problems In Engine Cycle Monitoring

PROBLEM AREAS	LINEAR SYSTEM ANALYSIS	PARAMETER SUBSET SELECTION	ADVANCED PERFORMANCE ANALYSIS
DATA ACQUISITION			
SENSOR NOISE	AVERAGED DURING MEASUREMENT	AVERAGED DURING MEASUREMENT	AVERAGED DURING MEASUREMENT AND MULTIPLE POINTS
SENSOR BIAS, NONLINEARITY	CONSTANT BIAS ONLY	CONSTANT BIAS ONLY	BIAS/SCALE FACTOR/OTHER AS REQUIRED
SENSOR DRIFT/RECALIBRATION	RECALCULATION OF BASELINE	NOT CONSIDERED	ESTIMATES BIAS PARAMETER
DISTURBANCE	NOT CONSIDERED	NOT CONSIDERED	MODELED AND/OR ESTIMATED AS REQUIRED
STABILIZATION/TRENDS	NOT CONSIDERED	NOT CONSIDERED	SPECIFICATION OF DATA DETRENDING
DATA RATE	NOT CONSIDERED	NOT CONSIDERED	TIME SERIES USED TO SPECIFY RATE
STORAGE REQUIREMENTS	SINGLE AVERAGED SCAN	SINGLE AVERAGED SCAN	MULTIPLE SCANS USED
SENSOR FAILURES	POST-PROCESSING FOR DETECTION	FAILURE MODE	MODEL USED TO PREPROCESS (VALIDATE) DATA
MEASUREMENT PROCESSING			
MODEL COMPLEXITY	POINT LINEARIZATION LINKED TOGETHER	SEPARATE MATRIX FOR EACH POWER	ONE FUNCTION MAPS ALL
MODEL ACCURACY/BASELINES	MORE ACCURACY, MORE MATRICES	MORE ACCURACY, MORE MATRICES	DIRECT ACCURACY/COMPLEXITY TRADE-OFF
BUILD VARIATIONS	CUSTOM BASELINE	CUSTOM BASELINE	INITIAL PARAMETER OFFSET
MODULE CHANGES	RECUSTOMIZE BASELINE	RECUSTOMIZE BASELINE	INCREASE CONFIDENCE LEVEL AND RE-ESTIMATE
MAINTENANCE EFFECTS	RECUSTOMIZE BASELINE	RECUSTOMIZE BASELINE	INCREASE CONFIDENCE LEVEL AND RE-ESTIMATE
CONTROL MODE EFFECTS	SMALL FLIGHT WINDOWS CHOSEN	SMALL FLIGHT WINDOWS CHOSEN	NONE
COMPUTATIONAL REQUIREMENTS	PROPORTIONAL TO SIZE OF DATA WINDOW	LARGE TO MASSIVE	COMPLEXITY MINIMIZED DURING DESIGN AND INDEPENDENT OF WINDOW

Table 2.11 (Continued)

PROBLEM AREAS	LINEAR SYSTEM ANALYSIS	PARAMETER SUBSET SELECTION	ADVANCED PERFORMANCE ANALYSIS
OUTPUT MANAGEMENT			
MAINTENANCE THRESHOLDS	NOT CONSIDERED	TUNED IN FIELD	DEVELOPED FROM AMT TYPE TESTING
FALSE ALARMS	NONE	ADDRESSED IN FIELD	LOW RATE
SCATTER IN RESULTS	PROBLEM AREA	FALSE ALARMS	CONFIDENCE INTERVAL CALCULATED
SOFTWARE MAINTENANCE	UNKNOWN	HIGH	LITTLE

these effects. Conservation of energy and mass are two input/output equations (see Figure 2.7) which relate parameters such as adiabatic efficiency and effective area to observed engine variables such as temperature and pressure (see Figure 2.6) [11]. A group of assumptions concerning the flow (e.g.. constant radial velocity gradients, constant specific heats, steady aerodynamics) are made in developing these nonlinear component models [11]. Verification of these data is usually accomplished from component rig testing. It is possible to use these equations as a performance model [12]; however, incremental process models are far more accurate and efficient for this purpose [13,14].

The effect of small deterioration processes on overall engine performance can be assessed using modern estimation methodology. In principle, each deterioration parameter is varied and the change in each output is tabulated. If it is assumed that (1) the parameters affect the outputs in direct proportion to their values and (2) the effects are independent of the other parameters, then the resulting equations are defined as a linear fault coefficient models [14,15]. These are most accurate for small changes in component characteristics such as those expected from the deterioration or aging process. Notice that the operating point about which perturations are measured must be fixed. Hence, the operating point (baseline) model and the fault models are complementary forms used to compare deteriorated measurements with nominal engine operation.

In order to be successfully integrated into the maintenance cycle, performance monitoring parameters must be directed to engine modules [16]. If a deteriorated or failed module is isolated at the intermediate (base) support level, existing maintenance and inspection procedures are geared to identify work items required to restore the component to an operationally satisfactory state [17], or specify shipment to the depot level maintenance area. Thus, the base level requirement for fault isolation to the module level originates. Further subclassification of the deterioration element (e.g., delineating between efficiency and area changes) does not improve the effectiveness of the maintenance outputs [17]. On the contrary, since the net error level is adversely affected by an increase in the independent deterioration parameters, estimating too many fault elements can significantly compromise system effectiveness.

2.2.3 Approaches to Measurement Processing

There are several approaches to the processing of performance data. In general, deviations result from shifts caused by deterioration and failure. These deviations are compared against fault parameters, and inferences concerning engine health are drawn. This sequence transforms measurements to health assessment indicators.

One monitoring approach detects consistent deviations in engine measurements; hence, it is termed the direct comparison method of failure detection. On-board monitoring procedures using this technique can be formulated for commercial aircraft [18,19]. The commercial flight envelope is dominated by steady-state cruise. If changes occur, this is indicative of a malfunction. This method requires little modeling and analytical data reduction. The arithmetic sign and magnitude of consistent deviations can be used to isolate common failure modes. Table 2.8 shows an example of a commercially implementable failure matrix designed for direct comparison isolation. Multiple faults, small deteriorations, and sensor bias shifts are more difficult to diagnose with such a system [18].

Alternately, a fault coefficient model can be used to invert the measured deviations and calculate an estimate of the deterioration parameters. This procedure is termed the inferential method [3]. The mathematical framework for the inferential method is the subject of Chapter III; however, the general concept is presented below.

Linear performance analysis is summarized in Figure 2.7. A group of p measurements, y, are recorded. An additional abscissa variable, u, is also measured. Curves or functions, $f(u)$, are used to represent normal engine operation as determined from a fleet average (generic) or from a particular (custom) engine's running levels. One such curve might be corrected rotor speed vs. EPR. A set of p deviations, Δy, is calculated as the difference in measured and baseline performance values as shown in Figure 2.7a. A linear coefficient model (Figure 2.7b) relates the deviations to engine parameter shifts, the q values of θ (e.g., fan efficiency or pumping capacity changes). The equations are inverted as shown in Figure 2.7c. This inversion can be imbedded in the more general parameter identification and filtering context and will be thoroughly treated in Chapter III. Table 2.9 summarizes some of the important aspects of this method.

If a single measurement is used in the linear performance analysis procedure (see Table 2.10), the parameter estimates are determined from a snapshot calculation. A snapshot estimate gives an indication of the engine status at a particular instant of time. The number of accurately detectable parameters must be smaller than the number of measured variables. Also, random and deterministic instrument errors can cause significant inaccuracies in the estimates [13,20].

To alleviate the severe instrument accuracy requirements of the snapshot approach, an alternative procedure can be applied. The filtering approach combines previous parameter estimates and new measurements to form both the optimal parameter estimates and estimates of error variance. Statistical analysis methods can be applied using these descriptors.

Extraction of trends in the parameter estimates and accurate quantification of the trends imbedded in data scatter are important secondary processes. Trends can be linked with engine life usage. While the level of component performance is a function of the engine build and particular physical dimensions, the change in its performance can be associated directly with deterioration. Special advanced mission and simulated mission endurance test programs can be used to measure observed parameter changes for components experiencing expected installed usage [21,22]. Trending parameters to measure changes as a function of usage and to predict when an allowable level is exceeded is an extremely attractive aid for maintenance policy formulation.

2.3 PRACTICAL ASPECTS OF CYCLE MONITORING ALGORITHMS

Practical issues associated with the monitoring problem will now be identified. These issues include data acquisition and storage, measurement processing and output management. Table 2.11 lists the important areas which must be addressed in each category and presents the monitoring methods which will be used to address these issues.

2.3.1 Three Areas of Practical Concern

Data acquisition generally involves the repeatable, accurate measurement of physical quantities in a harsh, dynamic operating environment over an extended period of time. The state of the art in transducer hardware and data recording systems addresses the physical aspects associated with these problems. Data processing must account for these error sources and produce results which minimize the inaccuracies. Random error due to sensor and channel noise can be reduced by averaging. Advanced algorithms filter the data and use groups of data points taken at different parts of the operating envelope to reduce error levels further. The best data rate can be established by an analysis of the noise in the measurement signal. The optimum number of sampled points is then derived [23]. Sensor failures are easily detected if they change significantly (hard-over). Leaks, shorts, and intermittent phenomena are more difficult to detect. In general, the use of the engine model to validate the set of measurements before the measurements are used to update the parameter estimates produces more accurate detection and isolation of sensor errors [24,25].

Problems caused by build variations and hardware changes (module swaps) during the engine lifetime must be addressed. Calculation of the operating baseline and sensor calibrations can be performed after each maintenance action. Alternately, a reinitialization of the confidence levels in the filter algorithm will discard information about unaffected parameters.

Output display is significant and has received the least attention in the development of current diagnostic systems. Decision processes can be statistically formulated and the optimum decision can be determined from the data. Often, the experience and judgement of the logistics manager is preferred to automatic decision outputs. Thus, performance estimates should be organized and displayed to allow human judgement to be exercised.

2.3.2 Thermodynamic Cycle Monitoring Methodology

The thermodynamic cycle monitoring approach [3] uses estimation algorithms to process engine performance data. These estimation algorithms are derived using maximum likelihood statistics. This principle simply states that, for a given set of data from an experimental process, there is a model which most likely generated that data. Many tractable maximum likelihood "methods" are based on the assumption that the model uncertainty is described by a Gaussian distribution. This assumption, combined with the assumption of an underlying linear model, has led to very effective data processing algorithms. Unfortunately, the engine model is highly nonlinear and the assumption of Gaussian statistics in descriptions of the model uncertainty is frequently not viable.

The theoretical basis of this formulation lies in simultaneous solution of both model equations and the likelihood criterion, and is presented in detail in Chapter III. Further extensions are required to integrate the presence of sensor errors. The thermodynamic cycle monitoring problem can be characterized by a few essential theoretical tasks.

There are three distinct aspects of the development process (see Figure 2.8).

(1) The development of quasi-linear regression models to match nominal and perturbed engine behavior.

(2) The selection of module-directed fault parameters based on acceptable error levels and system configuration.

(3) The use of the models in conjunction with a general maximum likelihood parameter estimation and trending algorithm to derive fault indicators from engine performance data.

2.4 SUMMARY

Engine monitoring has been discussed in general. A large number of health indices can be used to evaluate the status of an operating engine. Thermodynamic performance analysis has the potential to produce actual component directed health indicators, but the useful implementation of a

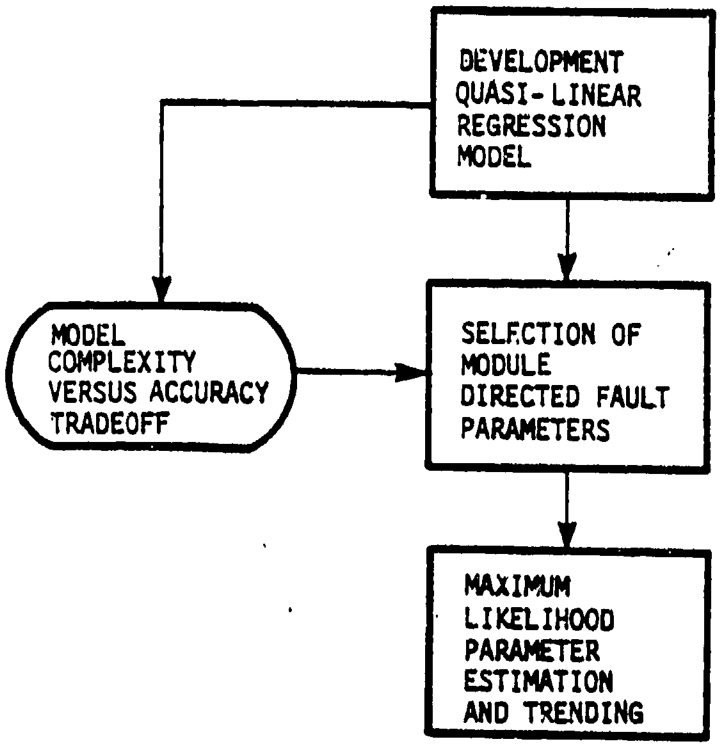


Figure 2.8 Development of Advanced Monitoring Algorithms

system requires careful design of the data acquisition, processing and presentation software. The thermodynamic cycle monitoring method discussed in more detail in the subsequent chapters rcpresents a system algorithmic framework from which a viable implementation can be derived.

III. MATHEMATICAL FOUNDATIONS OF THERMODYNAMIC CYCLE MONITORING (TCM)

3.1 INTRODUCTION

The previous chapter introduced the engine performance monitoring problem, current approaches to its solution, and some practical aspects that must be addressed by cycle monitoring systems. It is important to consider the general formulation of the data processing algorithm when deriving a procedure for handling the engine monitoring requirements. By specializing the general solutions, a generic methodology will evolve that is applicable over a wide class of engine, instrumentation, and processing hardware configurations. In this chapter, the general problem is formulated and algorithms for thermodynamic cycle monitoring are developed.

3.2 MODELING

The general theoretical requirements of the development are shown in Table 3.1. These requirements are driven by the general attributes of the overall monitoring problem (Table 3.2) to produce a family of algorithms that can be implemented within a group of hardware and data processing scenarios. The input/output requirements can be loosely represented as combining engine data and prior condition indices (Table 3.3) to form new condition indices and module or component-directed diagnostic indicators. The goals in formulation of the problem solution (Table 3.4) represent desirable features for a generic system, i.e., one that provides a large percentage of engine-type independent processing software and that can be flexibly altered, modified, and updated without significant programming impact. Linear models provide this type of manipulation flexibility, but do not achieve the accuracy levels in modeling installed engine performance.

The thermodynamic cycle monitoring (TCM) approach uses a generic baseline and fault parameter model combined into a class of algebraic equations known as quasi-linear regression (QLR) models. These models are nonlinear in engine

Table 3.1

General Theoretical Requirements

PROBLEM:	SPECIFY, ACQUIRE, AND PROCESS ENGINE DATA TO PROVIDE GAS PATH DIAGNOSTIC INDICES
SOLUTION:	INTEGRATE SENSORS, DATA PROCESSORS, DATA FORMATS WITH A SYSTEMATIC FRAMEWORK
YIELDS:	COMPREHENSIVE ALGORITHMIC STRUCTURE AND UTILIZATION METHODOLOGY

Table 3.2

Factors Driving The Selection Of A Theoretical Formulation

MODEL COMPLEXITY/CAPABILITY

ABILITY TO ISOLATE ENGINE AND SENSOR FAULTS IN REAL-TIME OR OFF-LINE ENVIRONMENT

ABILITY TO TREAT A VARIETY OF DATA SETS

DEMONSTRATED COMPATIBILITY WITH VARIETY OF DIGITAL PROCESSORS

UTILITY OF ALGORITHMIC OUTPUTS

Table 3.3

Fault Monitoring Problem

GIVEN:	1.	NOISY SETS OF MEASUREMENTS
	2.	PRIOR INFORMATION
PRODUCE:	1.	UPDATED ENGINE STATUS
	2.	FAILURE INFERENCES (ENGINE/SENSOR/CONTROL)
	3.	MODULE-DIRECTED INDICES
	4.	OPERATIONALLY SIGNIFICANT OUTPUTS

Table 3.4

Problem Formulation Goals

NONLINEAR REPRESENTATION OF GENERIC ENGINE BASELINE AND FAULT COEFFICIENTS -- CONTROL INDEPENDENT

INCORPORATES FLIGHT/POWER ENVELOPE CONTINUOUSLY

STANDARD MODEL FORMAT

EFFICIENT AND FLEXIBLE EVALUATION CAPABILITY

ACCURACY/COMPLEXITY TRADE-OFFS APPARENT

CORE CONSERVATIVE

operating point variables and linear in incremental fault parameters. A regression procedure is used to determine the particular model equations accurately for each engine type considered. The QLR model form and algorithmic implementation are chosen so that matrix-type operations can be performed on the nonlinear equations. This yields extremely efficient and flexible processing procedures that would otherwise be impossible at the same level of generality and model complexity.

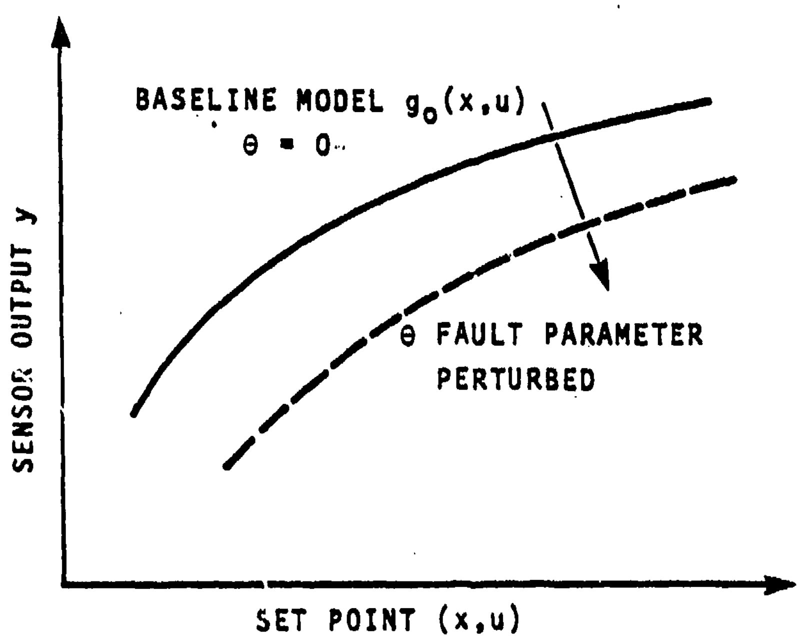
The quasi-linear engine model is assumed to be of the form:

$$y = g_0(x,u) + g_\theta(x,u)\theta + g_w(x,u)w + h_\phi(x,u)\phi + v \tag{3.1}$$

where

- y is a vector of sensed outputs (e.g. y_1 = PS3, y_2 = N2, ..., etc),
- x is the engine state vector,
- u is the control vector,
- θ is the deviation of linear fault parameters (e.g., fan efficiency, flow area, etc.) from the nominal,
- w is the deviation of disturbance parameters from nominal,
- ϕ is the instrument error parameters (e.g., bias, scale factor, etc.),
- v is random noise (e.g., channel noise, engine, disequilibrium, etc.)
- g_0 is the nonlinear polynomial baseline model,
- g_θ is the fault model,
- g_w is the disturbance model, and
- h_ϕ is the instrument error model.

The baseline model g_0 produces an estimate of the vector y for a nominal or average engine (i.e., $\theta = w = \phi = v = 0$) given x and u. It is assumed that the sensitivity of y to variations in the parameters θ, w, and ϕ is small when compared to the effects of state and control variables such as rotor speed and power lever angle. Thus, y can be modeled as a <u>linear</u> function of θ, w, and ϕ for a fixed operating point (x,u). However, the



$$y = g_0(x,u) + g_\theta(x,u)\theta$$

Figure 3.1 Graphical Illustration of the Engine Model functions g_θ, g_w, and h_ϕ may be <u>nonlinear</u> in x and u. Hence, Eq. (3.1) is called a <u>quasi-linear</u> engine model. Figure 3.1 illustrates a simplified version of Eq. (3.1). The equation structure models deterioration, instrument errors and disturbance effects as continuously varying functions of the operating point. The development of the quasi-linear model will be described next.

First, the development of a generic baseline model g_0 is described. The goal is to specify a function which accurately predicts sensed variables, y, for a nominal engine in the fleet. While a set of nonlinear thermodynamic equations could be derived from physical principles, the resulting equations would not match actual operating data very well. More accurate equations can be developed directly from the operating data. Since operating data do not represent perfect, noiseless observatons of a nominal engine, regression analysis is used to "average out" noise, errors, deterioration effects, etc. Regression analysis can determine nonlinear polynomial functions of a set of independent variables that best match, in a least-squares sense, a set of data points. In other words, the procedure fits analytical curves to the operating line data. While basic formulation of this method was developed several hundred years ago, recent analytical and computational results have significantly improved its accuracy and applicability.

The regression problem is to find a function $g_0(x,u)$ which minimizes the squared error between data points and the curve g_0. This problem can be expressed as

$$SS = \min_{g_0} \sum_{j=1}^{N} (\hat{y}^{(j)} - y^{(j)})^2, \quad \hat{y}^{(j)} = g_0(x^{(j)}, u^{(j)}) \tag{3.2}$$

where N is the number of observations, $y^{(j)}$ refers to the j^{th} observation of y. The predicted value of $y^{(j)}$ is called $y(j)$ given $x^{(j)}$, $u^{(j)}$. The quantity $\hat{y}-y^{(j)}$ is called the <u>residual</u> of the j^{th} observation. Note that Eq. (3.2) represents several regression problems simultaneously, one for each sensed variable y_i in the vector y. The first problem with this formulation is that the independent variables x,u are not perfectly known. These are replaced with observable quantities y. The second problem is that the form of the function g_0 (or y) must be specified. y must be chosen from a large number of nonlinear polynomial functions. The problem becomes one of choosing model terms from a large set of potential independent variables. The equations should be accurate (i.e. SS should be small) yet minimially complex (i.e., as few model terms as possible). Note that the sum of squares criterion SS is inversely related to the R^2 values: small values of SS correspond to large R^2 values. Techniques of optimal set regression which can identify the best set of explanatory (independent) variables among many possible subsets have recently been developed. These procedures have been implemented in the MODGEN (model generation) program [26].

The baseline model development consists of three major parts:

(1) data screening;

(2) calculation and selection of regression equations; and

(3) computer implementation and model validation.

The purpose of data screening is to produce a uniform data sample consisting of stabilized or repeatable data frames. Not all of the recorded data represent normal engine operating conditions because of sensor failures, outlier samples, equipment malfunctions, or other error. Because the regression procedure uses a sum of squares criterion, inclusion of outlier data could significantly bias the model computation. Little information is lost in this process when a large data population is used.

The screened data set is used as input to the MODGEN program for calculating selecting regression equations. Figure 3.2 shows the trade-off between model complexity and model accuracy. The point where the trade-off curve crosses the uncorrelated residual level is often the best choice for the number of model terms.

Figure 3.3 shows a graph of typical baseline model involving only one independent variable. The difference between the observations and baseline model predictions, i.e. the residuals, is plotted in Figure 3.4. Also shown in Figure 3.4 is the average fit error, σ. The value σ indicates the average error in the estimate $\hat{y}$ of the actual measurement y. The residuals should be randomly distributed about zero if the model is adequate.

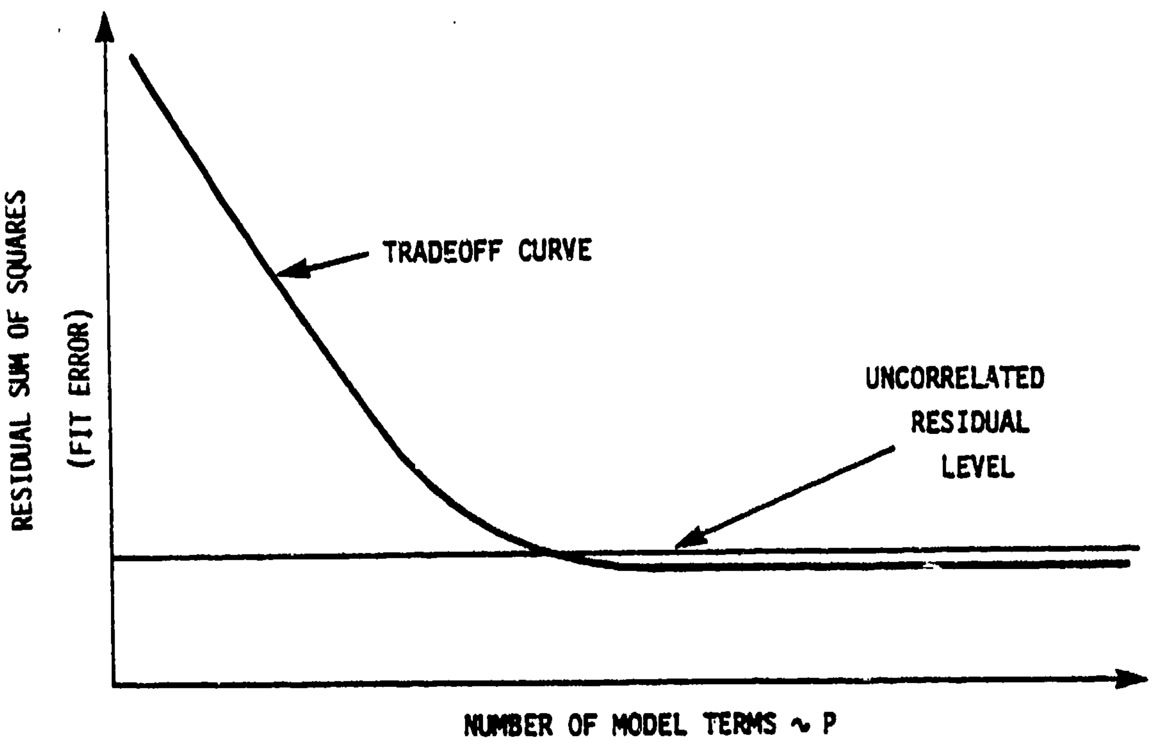


Figure 3.2 Model Complexity Versus Model Accuracy

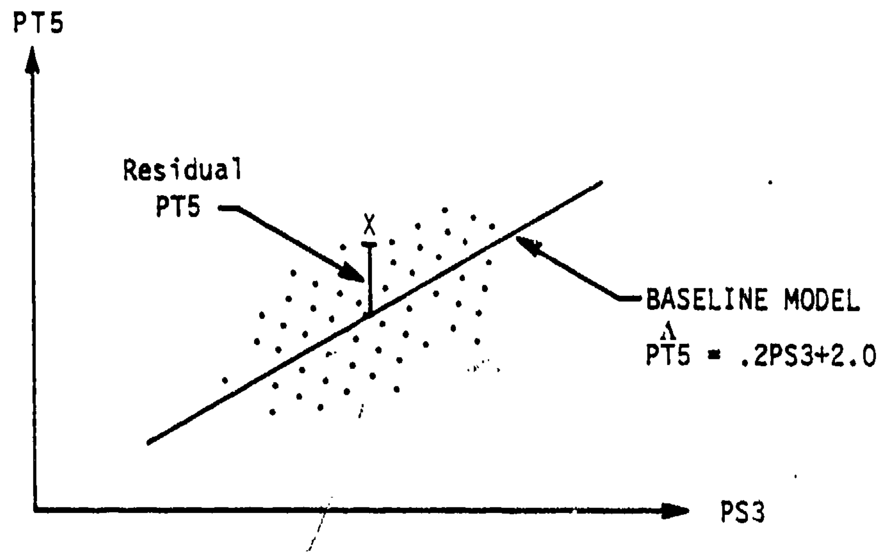


Figure 3.3 Screened Data With Baseline Model

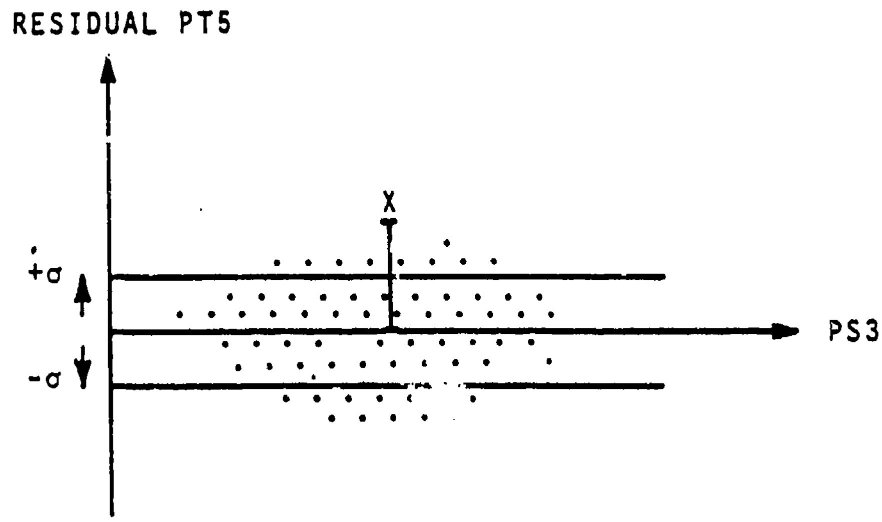


Figure 3.4 Residual Plot with Average Fit Error

$$\begin{array}{lcl} PS3 & = & -14.8\,PTO + 0.369\,PTO\,NF - .0558\,PTO\,T2C \\ (PSIA) & & + .0527\,PAMB\,NF - 4.00 \end{array}$$

$$\begin{array}{lcl} PT5 & = & .216\,PS3 + 2.04 \\ (PSIA) & & \end{array}$$

$$\begin{array}{lcl} ITT & = & .330\,WF - 36.3\,PTO - .0000344\,WF^2 \\ (^{o}C) & & -.018\,T2C\,PS3 + .424\,PTO\,T2C + 596 \end{array}$$

$$\begin{array}{lcl} NG & = & .409\,NF + .106\,T2C + 54.9 \\ (\Delta) & & \end{array}$$

$$\begin{array}{lcl} NF & = & .0975\,PS3 - .805\,PTO + .000638\,NG\,ITT \\ (\Delta) & & - .00296\,PAMB\,ITT + .0585\,PAMB^2 + 44.0 \end{array}$$

$$\begin{array}{lcl} WF & = & -.00597\,T2C^2\,NF + .147\,NF\,PS3 \\ (PPH) & & + .480\,T2C^2 - 210 \end{array}$$

$$\begin{array}{lcl} VG & = & 29.0 \\ (DEG) & & \end{array}$$

$$\begin{array}{lcl} T2C & = & 3.23\,NG - .0219\,WF - .0146\,PTO\,PS3 \\ (^{o}C) & & + .00673\,PTO\,ITT + .0716\,PTO\,NF - 306 \end{array}$$

$$\begin{array}{lcl} PTO & = & .510\,PT5 - .015\,ITT + .00329\,WF \\ (PSIA) & & + .0692\,T2C - .00519\,NF\,PT5 + 9.85 \end{array}$$

$$\begin{array}{lcl} PAMB & = & .0361\,PS3 + .0260\,WF - .000249\,WF\,NF \\ (PSIA) & & + .0000169\,WF\,T2C - .000166\,WF\,PTO - 5.16 \end{array}$$

$$\begin{array}{lcl} PLA & = & .00000417\,ITT^3 - .000070\,NG\,ITT^2 \\ (DEG) & & + 000315\,NG^2\,ITT - 64.3 \end{array}$$

Figure 3.5 A Typical Baseline Model

Approximately 68 percent of the residuals should fall in the interval $[-\sigma, +\sigma]$. A typical baseline model is shown in Figure 3.5.

Once the regression equations are chosen for each operating variable, the equations must be stored in the computer in an efficient manner. The computer representation of the model should minimize storage requirements, yet also permit systematic manipulation of the equations as needed by the TCM algorithms. The computer representation of a typical model is shown in Figure 3.6. The model shown in Figure 3.6 is a full engine model including the baseline model and fault models. The average fit error of the model is compared with the MODGEN calculations to validate the model. The validation procedure ensures that the model has been implemented correctly The methodology for generating the fault model will be described next.

The fault model g_θ expresses the effect of engine degradation (i.e., perturbing θ) on the sensor readings y (see Figure 3.1). Since the engine fault parameters are not directly observable, the fault model cannot be developed from operating data. In lieu of operating data, simulated data are generated from an engine status deck which solves the mechanical and thermodynamic equations for the engine. While simulated data may not very well match the baseline model derived from operating data, it is assumed that changes in the measurements caused by perturbing fault parameters are accurately reflected by the status deck.

To quantify the effect of decreasing fault parameters on the measurements y, two types of simulation data are generated. First, a nominal undeteriorated $(\theta = 0)$ configuration is modeled at a moderate number of conditions. Although the status deck models behavior in all parts of the operating envelope, operating data will be recorded in a significantly reduced portion. The specific conditions for data generation are chosen to match the range of data collected from the engine monitoring system. Subsequent data are generated at these same conditions, but with a single fault parameter, e.g. fan efficiency or turbine nozzle area, varied through representative values. Then the changes in the measurements Δy from their nominal configuration are recorded. These data are used to calculate the fault model g_θ.

```
                MODEL FOR EQUATION NUMBER    1
C=  .2487E-01   0000000010 0000000000 0000000000 0000000000 0000000000 0000000000
C= -.2277E+02   0000000001 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .7616E+00   0000000000 0000100000 0000000000 0000000000 0000000000 0000000000
C= -.1026E+03   0000000000 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .1444E+03   0000000000 0000000000 0000000100 0000000000 0000000000 0000000000
C= -.4043E-02   0000001000 0000000000 0000000010 0000000000 0000000000 0000000000
C= -.6150E+02   0000000000 0000000000 0000000000 0001000000 0000000000 0000000000
C= -.3031E+02   0000000000 0000000000 0000000000 0000001000 0000000000 0000000000
C= -.3985E+00   0000100000 0000000000 0000001000 0000000000 0000000000 0000000000
C= -.1362E-01   0000100000 0000000000 0000000000 0000000100 0000000000 0000000000

                MODEL FOR EQUATION NUMBER    2
C=  .7342E-01   0001000000 0000000000 0000000000 0000000000 0000000000 0000000000
C= -.4163E+01   0000000001 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .1779E+00   0000000000 0000010000 0000000000 0000000000 0000000000 0000000000
C=  .5055E-01   0000000000 0002000000 0000000000 0000000000 0000000000 0000000000
C=  .1928E+02   0000000000 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .1179E+01   0100000000 0000000000 0000000100 0000000000 0000000000 0000000000
C= -.4096E+00   0100000000 0000000000 0000000010 0000000000 0000000000 0000000000
C= -.5282E+00   0100000000 0000000000 0000000000 0001000000 0000000000 0000000000
C=  .2343E-01   0001000000 0000000000 0000000000 0000100000 0000000000 0000000000
C= -.7733E+01   0000000000 0000000000 0000000000 0000001000 0000000000 0000000000
C= -.1254E-01   0001000000 0000000000 0000000000 0000000100 0000000000 0000000000

                MODEL FOR EQUATION NUMBER    3
C=  .5046E-01   0000000010 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .8280E+00   0000000000 0010000000 0000000000 0000000000 0000000000 0000000000
C=  .8294E+00   0000000000 0000100000 0000000000 0000000000 0000000000 0000000000
C= -.7106E+02   0000000000 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .2553E+03   0000000000 0000000000 0000000100 0000000000 0000000000 0000000000
C= -.2127E+03   0000000000 0000000000 0000000010 0000000000 0000000000 0000000000
C= -.1114E-02   0010000000 0000000000 0000000000 0100000000 0000000000 0000000000
C= -.2845E+00   0010000000 0000000000 0000000000 0000010000 0000000000 0000000000
C=  .5021E+00   0001000000 0000000000 0000000000 0001000000 0000000000 0000000000
C= -.3684E+00   0010000000 0000000000 0000000000 0000100000 0000000000 0000000000
C=  .2466E+00   0000100000 0000000000 0000000000 0000001000 0000000000 0000000000
C= -.4131E+00   0010000000 0000000000 0000001000 0000000000 0000000000 0000000000
C= -.4255E+00   0001000000 0000000000 0000000001 0000000000 0000000000 0000000000
C= -.4053E-01   0000100000 0000000000 0000000000 0000000100 0000000000 0000000000

                MODEL FOR EQUATION NUMBER    4
C=  .7479E-01   0000000010 0000000000 0000000000 0000000000 0000000000 0000000000
C= -.4761E+02   0000000001 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .2140E+03   0000000000 1000000000 0000000000 0000000000 0000000000 0000000000
C= -.8761E-02   0000000000 0100000000 0000000000 0000000000 0000000000 0000000000
C= -.4274E+00   0000000000 0000100000 0000000000 0000000000 0000000000 0000000000
C= -.3520E+03   0000000000 0000000000 0000000000 0000000000 0000000000 0000000000
C=  .1114E+02   0100000000 0000000000 0000000100 0000000000 0000000000 0000000000
C= -.7082E+00   0001000000 0000000000 0000000000 0000010000 0000000000 0000000000
C=  .1859E+01   0100000000 0000000000 0000000000 0001000000 0000000000 0000000000
C= -.1146E+01   0001000000 0000000000 0000000000 0000100000 0000000000 0000000000
C=  .8055E+00   0001000000 0000000000 0000000000 0000001000 0000000000 0000000000
C= -.7575E+00   0001000000 0000000000 0000001000 0000000000 0000000000 0000000000
C= -.1701E+00   0001000000 0000000000 0000000000 0000000100 0000000000 0000000000
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Figure 3.6 Computer Representation of QLR Model

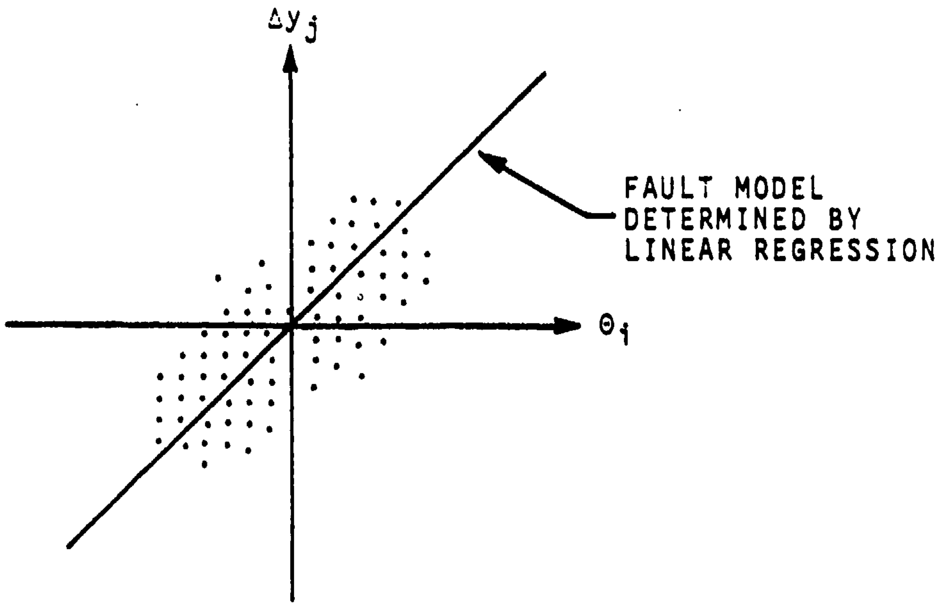


Figure 3.7 Fault Model Development

To illustrate this procedure, let Δy be the difference between y at the nominal configuration ($\theta = 0$) and y at the deteriorated configuration ($\theta \neq 0$). A typical data set generated by perturbing a single θ_i and observing the effect on y_j is shown in Figure 3.7. A regression procedure is then used to derive the fault model which best matches (i.e., minimizes the sum of squares) the simulated data. This regression is performed with the restriction that the models are linear in the fault parameters θ. If the fault parameter has an insignificant effect on the output quantity, the regression procedure will indicate this, and the corresponding terms will not be included in the fault model. The resulting model will then be in the quasi-linear form of Eq. (3.1). The fault model terms are then incorporated with the baseline model to produce a full QLR model. The model is again checked to verify that the computer implementation is correct. The model generation procedure is summarized in Figure 3.8. A typical QLR model for a single operating variable is shown in Figure 3.9.

The full QLR model forms the basis for an analysis to estimate the fault parameters, θ. However, since there are usually many fault parameters, a linear combination of these parameters will be estimated instead. The derivation of these module-directed fault parameters is described next.

3.3 PARAMETERIZATION

The goal of the estimation procedure, as described in Section 3.5, is to estimate meaningful engine health parameters accurately. Prior to the development of an estimate analysis, it is important to consider which parameters can and should be estimated. There are two major considerations in a parameterization procedure. First, it must be possible to estimate the parameters accurately. In general, as the number of parameters increases, the accuracy with which each can be estimated decreases. Second, the parameters should be physically meaningful and useful. The fault parameters discussed thus far have been rather general. Instrument parameters, cycle parameters, and disturbance inputs are available during the generation of the QLR model. In general, these are not the appropriate parameters to estimate from an

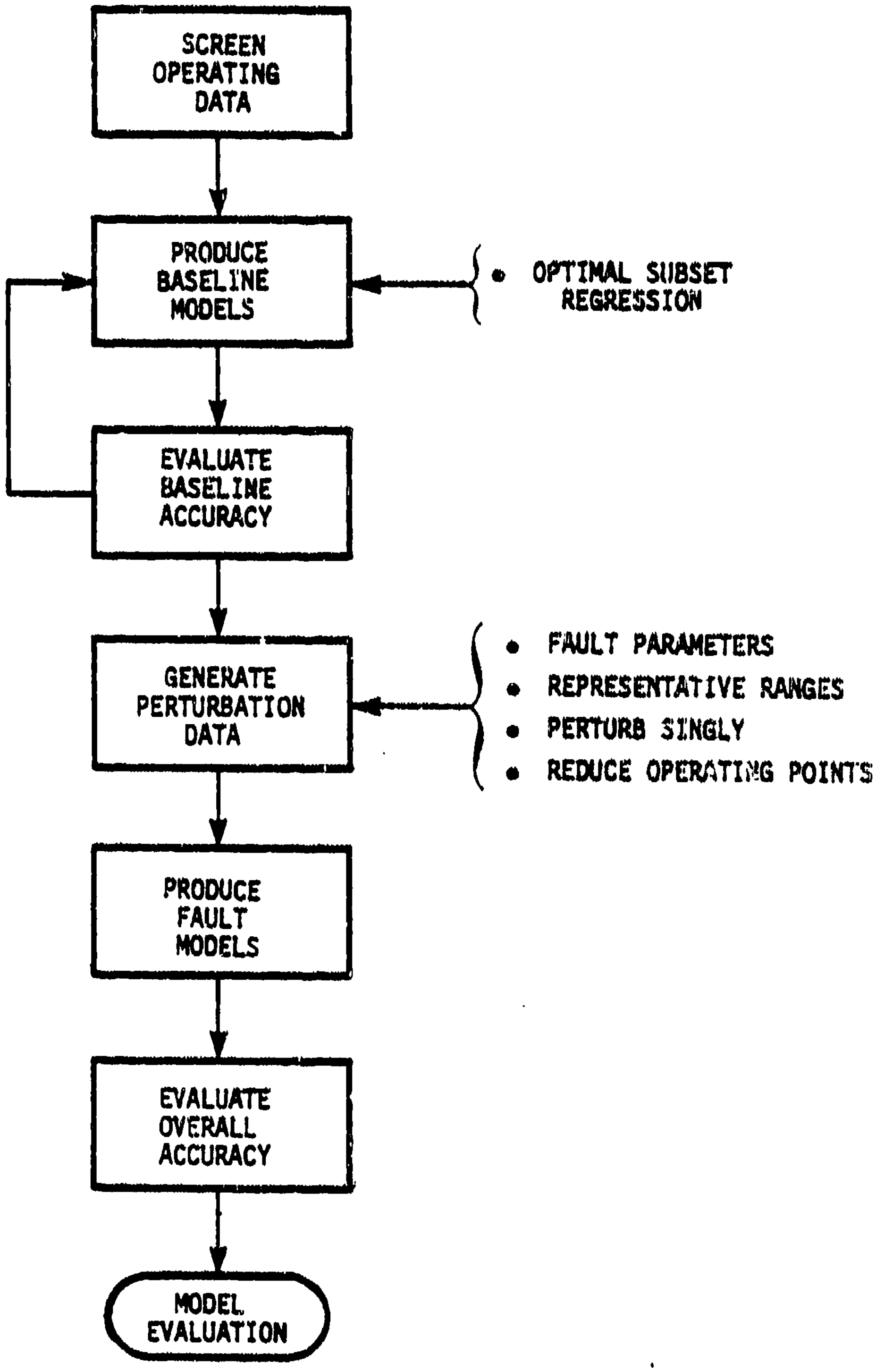


Figure 3.8 Model Generation Procedure

$$\hat{PT5} = \underbrace{.2PS3 + 2.1}_{\text{BASELINE MODEL}} \quad - \quad .1PS3e_1 + \underbrace{(-200 + 3.3NF)e_2 + .7PAMBe_4}_{\text{FAULT MODEL}} - .1PS3^2e_7$$

Figure 3.9 A Typical QLR Model

Table 3.5

Module-Directed Performance

PROBLEM:	MANY POSSIBLE FAULT PARAMETERS PRECLUDED ACCURATE ESTIMATION (UNIQUENESS PROBLEM)
OBSERVATION:	MAINTENANCE DECISION IS CONCERNED WITH PERFORMANCE OF A MAINTENANCE ITEM (OR MODULE)
QUESTION:	IS IT POSSIBLE TO COMBINE FAULT PARAMETERS TO FORM MODULE-DIRECTED PARAMETERS WHICH REFLECT MODULE STATUS AND CAN BE ACCURATELY ESTIMATED?

operational viewpoint in the sense that they present <u>too much</u> data to the maintenance personnel.

The candidate deterioration factors, e.g. areas and efficiency, were determined by the engine simulation. These may not represent efficient module-directed indicators. For example, the F100 core module contains the compressor, burner, and high-pressure turbine. These components are represented by five deterioration (fault) parameters. Condensing the information into one module-directed indicator increases the estimation accuracy. These considerations are summarized in Table 3.5.

An example of the method is shown in Figure 3.10 for a very simple problem. Initially, two parameters are to be uniquely estimated from a single measurement; this impossibility is manifested by a singular information matrix. However, a single <u>linear combination</u> of these parameters can be estimated. The increase in accuracy with the reduction in the number of variables is illustrated in this example.

A procedure for transforming the generating parameter set into a smaller set of hardware or module-directed parameters is derived below.

A general requirement for a reparameterization of the problem is shown in Figure 3.11. A transformation is calculated that increases the accuracy levels of the parameter set. The physical nature of the parameters will clearly place restrictions on the allowable combination of parameters. Thus, for example, a parameter measuring core gas path performance should be considered for a core-directed diagnostic display.

A method of geometric projection is used to derive a set of optimized, module-directed parameters. Consider a single, reduced parameter, θ, which will be some linear combination of a subset of the generating parameters,

$$\tilde{\theta} \subseteq \theta$$

This can be written as follows:

$$\tilde{\theta} = T^T \theta$$

$$T = [t_1, \ldots, t_r, 0 \ldots 0]$$

where it has been assumed that $\tilde{\theta}$ is a function of the first r θ values. The subspace of parameters (r dimensional) spanned by the r allowable parameters will contain the optimal $\tilde{\theta}$. The linear combination, $\tilde{\theta}$ (which will be restricted to pure rotations to avoid distortion of the metric), will

MODEL: $y = \theta_1 + 2\theta_2 + v$ $\quad$ $v: N(0,1)$

INFORMATION MATRIX: $M = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$

DISPERSION: $COV(\theta) = M^{-1} = \infty$

TRANSFORMATION: $\tilde{\theta}_1 = \theta_1 + 2\theta_2$

$\tilde{\theta}_2 = 2\theta_1 - \theta_2$

NEW DISPERSION: $COV(\tilde{\theta}) = \begin{bmatrix} 5 & 0 \\ 0 & 0 \end{bmatrix}$ $\quad$ OR

$COV(\theta_1) = 1/5$

Figure 3.10 Module-Directed Performance Example

ESTIMATION ACCURACY: $\mathrm{COV}(\tilde{\theta}) = M^{-1}$

PARAMETER TRANSFORMATION: $\tilde{\theta} = T^T\theta$

MODIFIED COVARIANCE: $\mathrm{COV}(\theta) = T\tilde{M}T^T$

$$= \tilde{M}$$

DECOMPOSITION:

$$\tilde{M} = \begin{bmatrix} \tilde{M}_{11} & \tilde{M}_{12} \\ \tilde{M}_{21} & \tilde{M}_{22} \end{bmatrix}$$

Choose T such that $\mathrm{COV}(\tilde{\theta}_1) << \mathrm{COV}(\tilde{\theta}_2)$

Then estimate only θ_1:

$$\mathrm{COV}(\tilde{\theta}_1) = M_{11}^{-1} + M_{11}^{-1} M_{12}\, \mathrm{COV}(\tilde{\theta}_2)\, M_{21} M_{11}^{-1} \approx M_{11}^{-1}$$

Figure 3.11 Module-Directed Performance Parameters

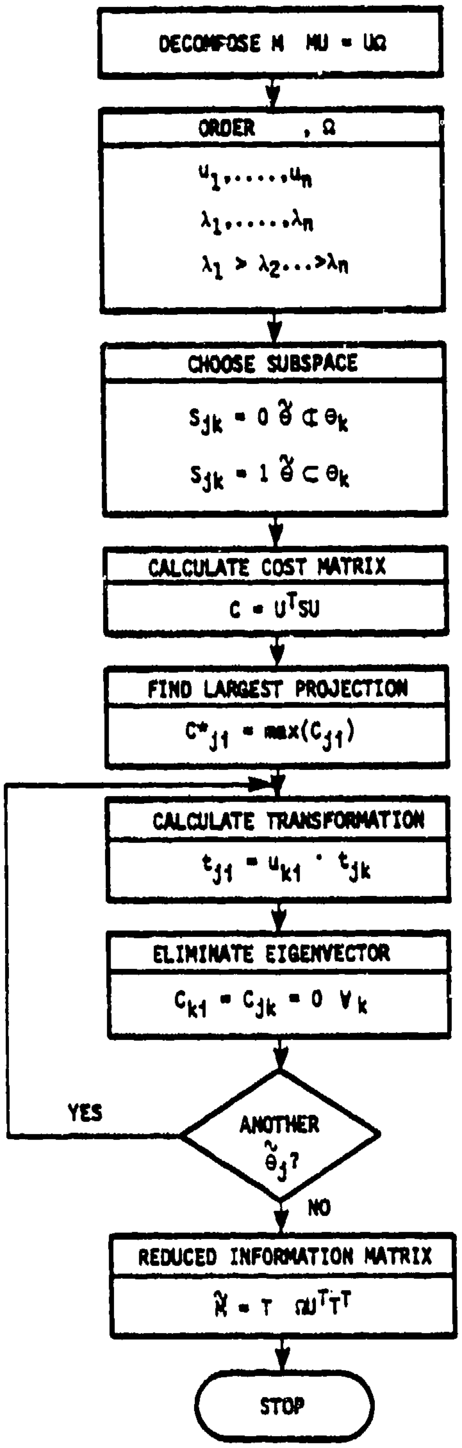


Figure 3.12 Parameter Projection Decomposition

have the largest projection in the direction of the largest eigenvalue of M (i.e, in the eigendirection of that eigenvalue) of any vector in the subspace. Calculation of this projection will produce the required rotation and the required reducing transformation, T.

The procedure can be extended to a large number of reduced parameters by ranking the largest projection on the largest eigenvalues of M and sequentially selecting rotations and eliminating eligible eigenvectors. This projection method has been implemented and is shown in Figure 3.12. The final result will be a set of module-directed TCM parameters that represent subsets of the original set, or

$$\underset{(rx1)}{\tilde{\theta}} = \underset{(rxq)}{T} \cdot \underset{(qx1)}{\theta}$$

The physical interpretation of this procedure is that information concerning estimated parameters is processed in the most favorable combination from a structural viewpont. If the sensor set is not inclusive enough or does not contain sufficiently accurate probes, unique estimates of all cycle parameters will not be available from <u>any</u> estimation method. It remains to select linear combinations of parameters that have a physical interpretation in the engine. This can be illustrated as follows. Suppose that a parameter directed toward the high-pressure turbine were calculated as follows:

$$\tilde{\theta}_{HT} = a_1 \Delta A_{HT} + a_2 \, \Delta\eta_{HT}$$

i.e., the reduced parameter is a combination of the efficiency and area change of the component. Under normal operating conditions, an aging turbine will exhibit a decrease in efficiency and an increase in effective area due to erosion, seal leakage, and other microscopic processes. Clearly, unless a_1 and a_2 are opposite in sign, the effect on the module- directed turbine parameter will be attenuated. Thus, the projection procedure result must be evaluated vis a vis the nature of observed deterioration modes to verify the appropriateness of the selected reduced parameter identity. Adjustments in the parameterization may be made by forcing alternate projections to be selected in the calculation process.

A group of parameter evaluation methods have been reviewed. The QLR model can be manipulated using these transformations into a form that will produce optimal, module-directed estimated parameters from the TCM algorithm. In the last section, a sensor validation procedure is presented that uses the identified engine model as a basis for diagnosis of failed sensor inputs in a new set of data.

3.4 SENSOR VALIDATION

An important consideration in processing engine health monitoring data is the detection and isolation of data scans that include failed or disconected channels. In addition to actual probe failure, uninstalled engine run data often will not have a full data complement. In practical operation, sensor channels may remain failed for long periods of operating time because a maintenance opportunity has not arisen. In order to include partially failed data in the processing, some form of detection and reconstruction is desirable. The general cross- validation procedure discussed below represents an efficient and accurate algorithm built on the flexibility of the QLR design and the accuracy levels associated with the parameter identification process. These attributes are summarized in Table 3.6.

The sensor validation algorithm preprocesses sensor measurements, in conjunction with the estimated QLR models, to determine if the measured values are statistically consistent with previously measured values. Parameter estimate uncertainties are used to establish the testing threshold. Since these are reset by maintenance activity, threshold values are adaptively changing to the uncertainty in the model. False alarm rates are low. Inconsistent data channels are flagged as sensor failures and the sensor data value is calculated. This process accommodates intermittent channel failures without modification of the estimation process.

Table 3.7 illustrates the process on a linear model. A test variable (which is normally distributed) is estimated and exceedances are detected. Failed channels are discarded and the model is used to generate new test variables. The process iterates until the failed channel coincides for two iterations. Clearly, this process cannot be successfully completed for a general set of instrument failures. The conditions will allow a stable reconstruction of the failed channels from the unfailed channels to determine

Table 3.6

Sensor Diagnostic Algorithm

DATA PREPROCESSING

REJECTION OF OUTLIERS/FAILED CHANNEL DETECTION

RECONSTRUCTION OF FAILED CHANNEL FOR FILTER

PROVIDES ABILITY TO PROCESS INCOMPLETE SENSOR SETS

Table 3.7

Sensor Diagnostics - General Cross-Validation Linear Case

STEP 1: DETECTION

$x = Ax + w$: $N(0,Q)$

$\hat{y} = Ay$ Measurements

$y = x + v$ v: $N(0,R)$

$\delta y = y - \hat{y}$ Test Variable

DEFINE:

$$\alpha_i^2 = \mathrm{DIAG}\ ((I-A)R(I-A)^T + Q)$$

$$|\delta y| \begin{cases} <3\alpha_i & \text{NORMAL} \\ >3\alpha_i & \text{OUT-OF-RANGE} \end{cases}$$

STEP 2: ISOLATION (IF THERE ARE ANY OUT-OF-RANGE CHANGES)

$$\begin{bmatrix} \hat{y}_1 \\ \hline \hat{y}_2 \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ \hline A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} y_1 \\ \hline y_2 \end{bmatrix} \quad \begin{array}{l} \text{OUT-OF-RANGE} \\ \text{NORMAL} \end{array}$$

$$\begin{array}{l} \delta y_1 = y_1 - \hat{y}_1 \\ \delta y_2 = y_2 - \hat{y}_2 \end{array} \quad \text{MODIFIED TEST VARIABLES}$$

GO TO STEP 1 UNTIL OUT-OF-RANGE AND NORMAL SETS MATCH

STEP 3: RECONSTRUCTION

SET $y_1 = \hat{y}_1$

the set of isolatable channel failures. This condition may be restated as a mathematical condition on the model matrix A as follows. The system of p sensor channels will be r isolatable if every rxr submatrix of the model A is invertible. In general, the rank of the model matrix will be p-m where m is the number of independent setting parameters of the engine which are me ensors, e.g., in the F100, PT2, TT2, and PLA are required to set the oper ing point. Thus, at most, 8 out of 11 sensor channels will be isolatable at a given linearization point. In practice, the structure of A will be such that many failure combinations of up to six sensor failures can be accommodated by the procedure. This practical limit is above that which is normally encountered in installed and uninstalled data. If a particular sensor scan cannot be isolated, the algorithm will indicate that all channels have failed and the data can be discarded.

The model used to validate the channels is the QLR representation including sensor and parameter variance estimates. If a channel fails, the reconstructed channel is formed from the a priori model. Therefore, no inconsistent information is passed into the estimator and the effect of channel failures will be automatically accommodated. This feature allows the estimation algorithm to be independent of the sensor diagnostics, which can considerably increase the flexibility of the software.

The nonlinear model procedure is illustrated in Table 3.8. The method is identical to the linear case with the linearizations at the operating point used. The thresholds are calculated from sensor and parameter uncertainty levels. They are recalculated for each failure configuration. The calculation does not require additional linearizations, but rather proceeds from a simple column operation on the initial linearized matrices. The calculations described in the table are supported by the same QLR software that is used in the parameter estimation routines. This factor makes the implementation of the generalized cross-validation procedure viable. The flow diagram for this procedure is shown in Figure 3.13.

The threshold levels range between 5 percent and 10 percent of the measured value. The me hod has been verified to detect correctly an arbitrary set of out-of-tolerance channels. Table 3.9 illustrates an iteration to detect a low N_1 reading. During the first pass using the low N_1

Table 3.8

General Cross-Validation (Nonlinear Case)

CONSIDER SPLITTING VARIABLES INTO TWO GROUPS:

$x_1 \Rightarrow$ OUT-OF-BOUNDS CHANNELS

$x_2 \Rightarrow$ NORMAL CHANNELS

ISOLATION EQUATIONS:

$$\bar{x} = y - h_\phi(\bar{x})\hat{\phi}$$

$$x = g_0(\hat{x}_1, x_2) + g_\theta(\hat{x}_1, \bar{x}_2)\hat{\theta}$$

LINEARIZATION TO DETERMINE VARIANCE:

$\delta x = \hat{x} - \bar{x}$ ERROR TERM

$$\begin{bmatrix} \delta x_1 \\ \delta x_2 \end{bmatrix} = \left[\begin{array}{c|c} I - g_{011} - g_{\ 11} & 0 \\ \hline -g_{021} - g_{\ 21} & 1 \end{array}\right] \left[g_\theta \theta - g_w w - (I - g_0 - g_{\theta x}\hat{\theta})^{-1} (I + h_\phi \hat{\phi})^{-1} (v - h_\phi \phi) \right]$$

WHERE

$$g_{021} = \frac{\partial}{\partial x_1} g_{02}$$

SIMPLIFYING EXPRESSION:

$$F = I - g_0 - g_{\theta x}\hat{\theta}$$

$$B = I + h_{\phi x}\hat{\phi}$$

$$\tilde{F} = \left[\begin{array}{c|c} I - g_{011} - g_{\theta 11}\hat{\theta} & 0 \\ \hline -g_{021} - g_{\theta 21}\hat{\theta} & 1 \end{array}\right]^{-1}$$

$\tilde{F}$ IS FORMED FROM F BY REPLACING COLUMNS OF NORMAL CHANNELS WITH UNIT VECTORS

Table 3.8 (Continued)

$$\delta x = \underbrace{\tilde{F}[g_{\theta} \mid FB^{-1}\, h_{\phi} \mid -g_{w} \mid -FB^{-1}]}_{Q} \begin{bmatrix} \theta \\ \phi \\ w \\ v \end{bmatrix}$$

$$= Q\Delta$$

UNDER ESTIMATION ASSUMPTIONS, Δ IS ZERO MEAN, NORMALLY DISTRIBUTED RANDOM VECTOR, i.e.

$$\delta x : N(0, Q\Delta Q^T)$$

$$\Delta = COV(\Delta)$$

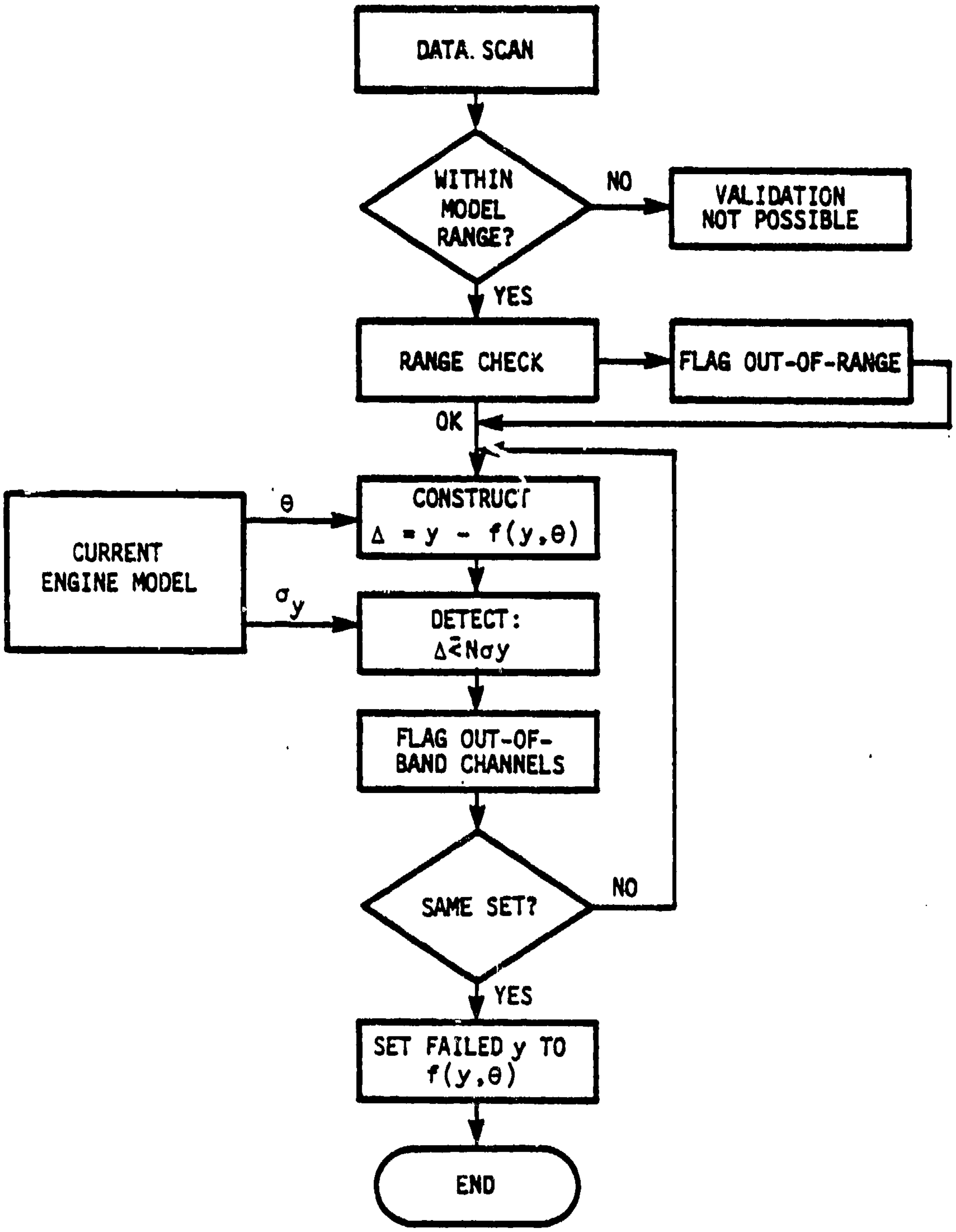


Figure 3.13 General Cross-Validation Processing Flow

Table 3.9

Sensor Failure Detection Example - N_1 Sensor Low

		ITERATION 1			ITERATION 2				
CHANNEL	(UNITS)	FAILURE INDICATION	ΔSENS	THR	FAILURE INDICATION	ΔSENS	THR	FAILED POINT	PROCESSED POINT
TT25	(°R)		-2.4	27		-1.1	27	766	766
PT25	(PSIA)	X	-11	6.0		-0.7	5.7	35.5	35.5
TT3	(°R)	X	-190	27.0		-3.0	101	1485	1485
PT4	(PSIA)	X	-157	18.0		-0.4	60	275	275
TT45	(°R)		1.0	165		-1.3	270	2167	2167
PT6	(PSIA)	X	-12	2.1		0.2	6.1	33.9	33.9
WF	(PPH)	X	-2073	990		-44	2700	8166	8166
N_1	(RPM)	X	2010	740	X	2000	750	8083*	10091
N_2	RPM)	X	-2460	1500		19	600	12957	12957

* ACTUAL = 10083 RPM

T_{T2}
ARE KNOWN
P_{T2}

Table 3.10

Sensor Validation Algorithm

- USES ENGINE MODEL DERIVED FROM OPERATING DATA INCLUDING CHANNEL ERROR VARIANCE
- USES RANGE CHECKS FOR HARD FAILURES
- USES CHANNEL ERROR STATISTICS FOR SOFT FAILURES
- DETECTS MULTIPLE FAILURES WITHOUT FAULT TREE
- ESTIMATES FAILED CHANNEL READING FOR SUBSEQUENT DIAGNOSTIC UTILIZATION

reading, seven channel failures are detected. The sensor deviation and threshold are shown in the table. On the second pass, the two in-bound channels are used to solve for the remaining seven channels. The thresholds are adjusted to account for the loss of precision in this process. On the second and subsequent pases, one N_1 is out of tolerance and this channel is reconstructed. These data represent actual F100 operating data. Results discussed in Chapters V and VI are extremely promising.

A sensor diagnostic routine that uses a general cross- validation procedure has been described. The attributes of the algorithm are summarized in Table 3.10. The algorithm is supported directly with the QLR software library and provides a powerful capability without a large software commitment.

3.5 ESTIMATION

This section presents the development of an algorithm designed to estimate the module-directed rating parameters. (To simplify the notation, these reduced parameters will be denoted by $\tilde{\theta}$ rather than θ.) The performance estimation flow path is summarized in Figure 3.14. Data scans are checked for sensor failures by the sensor validation algorithm. If there are failed channels, only these are reconstructed. Using the baseline model, the residual measurements Δy are computed. The values Δy represent the difference between the observed measurements y and the values $\hat{y}$ which are the predicted values for a nominal engine. This residual vector is passed to the estimation routine which produces an estimate $\hat{\theta}$ of the module-directed rating parameters. The covariance of the estimates are updated and the process repeated until the estimate has converged.

The formal development of a QLR model for engine performance culminates in an easily linearized equation (Eq. (3.3)) which relates the sensitivity of the sensor outputs to fault parameter variations, disturbances, and instrument effects.

$$\hat{\Delta y} = H\Delta\theta + v \tag{3.3}$$

The processing of measurements to derive accurate estimates of the parameter values is the function of the filtering algorithm. The precise algorithm used to filter the data is strongly influenced by the type,

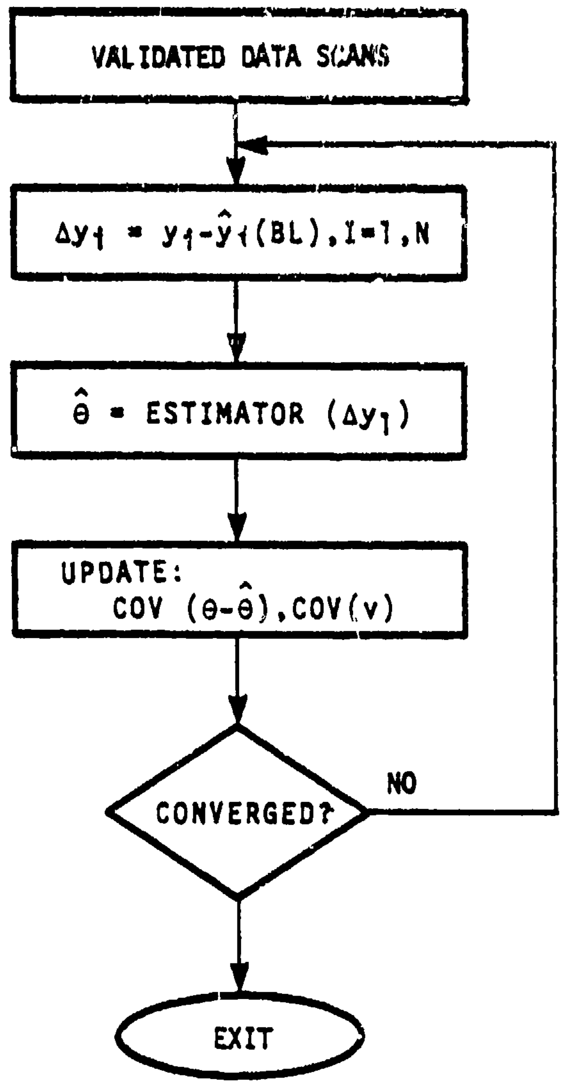


Figure 3.14 Performance Estimation Flowpath

frequency, and accuracy of the measurements. The processing environment, operating scenario, and data interfaces also impact this procedure. Several different methods are outlined below and a routine that has been specifically developed for processing off-line performance data is presented.

Suppose the problem is approached for the solution of Eq. (3.3) by inverting the measurement matrix, H, i.e.

$$\Delta\theta = H^{-1}\,\Delta y \tag{3.4}$$

Direct inversion of H is possible only when the number of parameters equals the number of measurements. It is usually possible to formulate the model so this condition is met. However, a more subtle numerical effect is presented in Eq. (3.4). During system development, the error sources, v, have been maintained at an acceptably low level, but their effect on the parameter estimates may not be small. This property can be quantified by the <u>condition number</u> of H. The condition number is defined as the ratio of the maximum to minimum eigenvalue of H, or

$$\rho(H) = \log\left\{\frac{\lambda_{max}(H)}{\lambda_{min}(H)}\right\} \tag{3.5}$$

where $\lambda(H)$ is the modulus (magnitude) of an eigenvalue of H. Intuitively, it represents the magnification possible in matrix multiplication. For example, a matrix H with condition number 3 could conceivably magnify a 0.1 percent sensor error into a 100 percent error in a parameter estimate.

Before considering this effect further, the inversion in Eq. (3.4) can be generalized to include the case when the number of parameters is less than the number of measurements as follows:

$$\hat{\Delta\theta} = (H^T H)^{-1}\,H^T \Delta y \tag{3.6}$$

This reduces to Eq. (3.4) if H is square and invertible. Equation (3.6) is the <u>least-square</u> (LS) solution to Eq. (3.3). If v is considered a random noise process (e.g., Gaussian, zero mean, or $N(0,R)$, then its covariance is written:

$$\mathrm{cov}(\Gamma v) = \Gamma R \Gamma^T \tag{3.7}$$

The LS inverse (Eq. (3.6)) can be modified to form the weighted LS estimate within the statistical framework as follows:

$$\hat{\Delta\theta} = (H^T \Gamma^T R^{-1} H)^{-1} H^T \, {}^T R^{-1} \, y \tag{3.8}$$

Using Eqs. (3.7) and (3.8), the uncertainty in the parameter estimate caused by the noise can be written as follows:

$$\mathrm{cov}(\Delta\theta) = (H^T \, R \, {}^T H)^{-1} \tag{3.9}$$

The matrix $(H^T \, R \, {}^T H)^{-1}$ is termed the <u>dispersion</u> of the estimator

$$D = (H^T \Gamma R \Gamma^T H)^{-1} \tag{3.10}$$

The <u>information matrix</u> for this estimate is defined as the inverse of the dispersion, or

$$M = D^{-1} \tag{3.11}$$

Intuitively, if M is "large," the estimation error covariance will be small. The size of M can be specified, in part, by its condition number.

The LS estimation process that arises from considering v a Gaussian, zero mean error source is <u>weighted least squares</u> (WLS). The formula for the WLS estimate is as follows:

$$\hat{\Delta\theta} = M^{-1} H^T R^{-1} \Delta y \tag{3.12}$$

This estimator produces the maximum likelihood or highest probability value for $\Delta\theta$ given a single set of measurements and assuming a known Gaussian error.

The estimator in Eq. (3.12) is used as the basis for a <u>snapshot</u> estimator in current GPA algorithms. A number of technical issues must be resolved before accurate results can be obtained. Some important problems are bias levels in the sensors, errors in measuring the operating point, too many parameters to estimate, and poorly conditioned information matrices.

The WLS estimator addresses the snapshot processing problem. The simplest filtering scenario employs sequential processing. Here, a measurement is available for processing once. Prior information about the parameters may be available and include the last estimates and their covariances. The measurement is processed, the parameter estimates updated, and the data discarded. This scenario is common in on-line data processing. The WLS form can be extended to sequential filtering. If the noise statistics are known, the resulting algorithm is known as the Kalman filter [27].

The important advantage of this processing scenario concerns the noise attenuation properties of the estimator. This may be illustrated using the WLS information matrix defined in Eq. (3.11). It can be shown that for N groups of data, the resulting WLS dispersion can be approximated by the following expression:

$$D = \left[\sum_{i=1}^{N} M_i \right]^{-1} \tag{3.13}$$

where M_i is the information matrix for the i^{th} set of data. Thus, the matrix M measures the accumulation of information about the parameters. The obvious implication is that, in general, the more data used, the more accurate the parameter estimates. Also,

$$M_i \neq M_j \tag{3.14}$$

i.e., if different operating points are chosen for data acquisition, it is possible that the condition number of the net information matrix will be smaller than the individual terms. Physically, this represents the combination of information about different parameters at different flight points. Stated another way, it is possible that more parameters than measurements can be estimated. When this is the case, important sensor error parameters can be included in the estimator to improve overall accuracy.

This filter produces accurate results when (1) the parameter values are constant and (2) the error covariance is stationary and white. There is no "check" of the actual accuracy from an on-line evaluation. Also, as the number of data points becomes large, the estimator tends to be "oblivious" to new information due to the large certainty attached to the prior parameter estimates.

Snapshot and sequential processing have been discussed. The more appropriate scenario for TCM involves repetitive processing of a group of data points. This method is often defined as off-line and is shown schematically in Figure 3.15. Starting with prior estimates and statistics of the parameters, a group of data points is iteratively used in the calculation. After processing is complete, the data are discarded and the updated estimates and statistics are stored.

An algorithm has been developed for the data processing scenario described above. The measurement equation can be written as follows:

$$\Delta y = H(x,u)\Delta\theta + v \qquad (3.15)$$

where v is a normal, Gaussian sensor and disturbance vector with

$$v = N(0,R).$$

Specific elements of the y, θ, and v vector have been discussed in the previous sections. The best estimate of the parameters θ, for a set of measurements can be found from a minimization of the likelihood function given as follows [28]:

$$J = \sum_{i=1}^{N} (\Delta y(k) - H(\hat{x},u)\,\hat{\theta})^T \hat{R}^{-1} (\Delta y(k) - H(\hat{x},u)\hat{\theta})$$

$$+ (\theta - \theta_0)^{-1} M^{-1} (\theta - \theta_0)$$

where the last term represents the a priori covariance of the parameter estimates. The necessary conditions for a minima are given as follows:

$$\left.\frac{\partial J}{\partial x_k}\right|_{\hat{x}_k,\hat{\theta}} = 0$$

$$= H_x^T(k) R^{-1} (\Delta y_k - H(k)\theta) \qquad k = 1,\ldots,N$$

$$\left.\frac{\partial J}{\partial \theta}\right|_{\hat{x}_k,\hat{\theta}} = 0$$

$$= \sum_{i=1}^{N} H^T \hat{R}^{-1} (\Delta y_k - H(k)\hat{\theta}) + M^{-1}(\hat{\theta} - \theta_0)$$

where

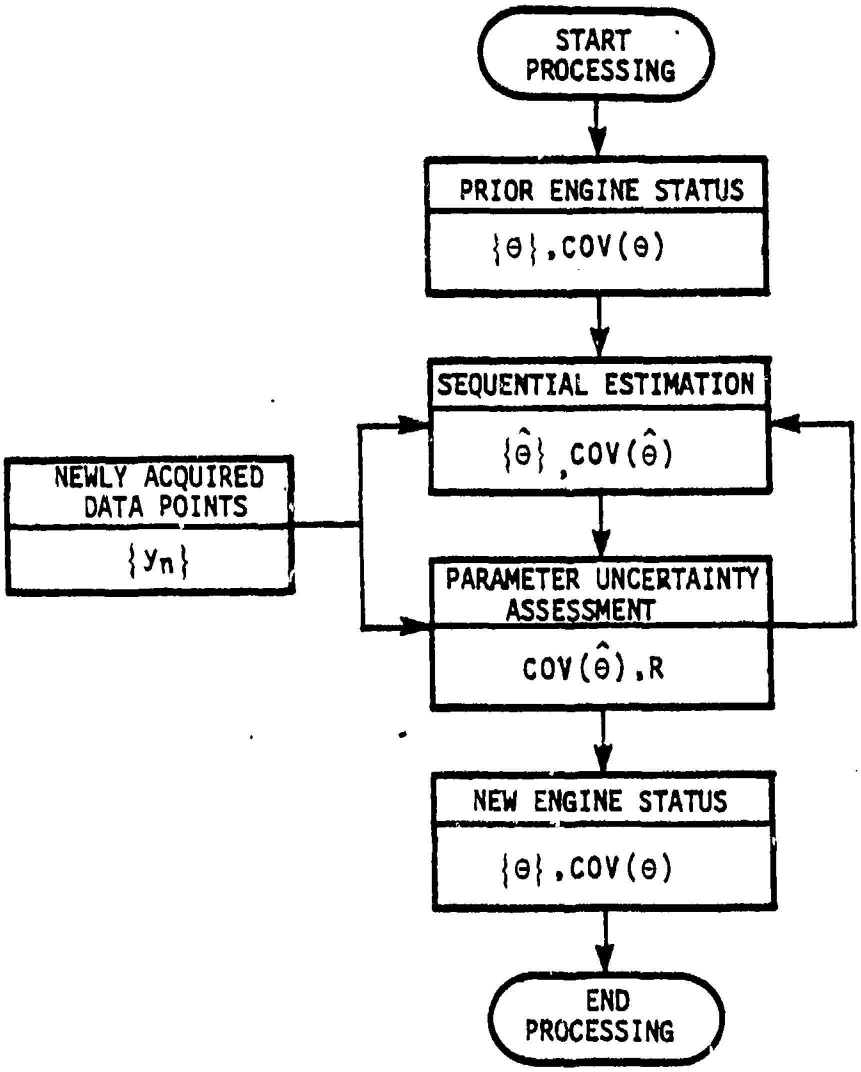


Figure 3.15 Off-Line Processing Scenario

$$H_x(k) = \left.\frac{\partial H(x,u,\theta)}{\partial x}\right|_{\hat{x}_k,\hat{\theta}}$$

$$H(k) = H(\hat{x},u,\hat{\theta})$$

The smoothing solution to the problem can be written as follows [28]:

$$y = \begin{bmatrix} \Delta y_1 \\ \hline \Delta y_2 \\ \hline \vdots \\ \hline \Delta y_n \end{bmatrix}$$

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}$$

$$H(x,u) = \begin{bmatrix} H(x_1, u_1) \\ \vdots \\ H(x_N, u_N) \end{bmatrix}$$

$$H_x = \frac{\partial H}{\partial x} = \begin{bmatrix} H_x(1) & & 0 \\ & \ddots & \\ 0 & & H_x(N) \end{bmatrix}$$

$$\hat{R} = \begin{bmatrix} \hat{R} & & 0 \\ & \ddots & \\ 0 & & \hat{R} \end{bmatrix}$$

Then, in principle, a Newton-Raphson iteration [29] can be applied as follows:

$$z_{i+1} = \left[\frac{\partial^2 J}{\partial z^2}\right]^{-1} \frac{\partial J}{\partial z} + z_i$$

$$\begin{bmatrix} \hat{x}^{i+1} \\ \hat{\theta}^{i+1} \end{bmatrix} = \begin{bmatrix} \hat{x}^i \\ \hat{\theta}_i \end{bmatrix} + \left[\begin{array}{c|c} H_x^T\hat{R}^{-1}H_x & H_x^T\hat{R}^{-1}H \\ \hline H^T\hat{R}^{-1}H_x & H^T\hat{R}^{-1}H + M^{-1} \end{array}\right]^{-1}$$

$$\begin{bmatrix} H_x^T \hat{R}^{-1} (\Delta y^i - H(\hat{x}^i, u)\theta^i \\ \\ H^T \hat{R}^{-1} (\Delta y^i - H(x^i)\hat{\theta}^i) + M^{-1}\ \theta^i \end{bmatrix}$$

and at each step, $\hat{R}$ can be calculated as follows:

$$\hat{R} = \frac{1}{N} \sum_{i=1}^{N} (\Delta y^i - H(x^i, u)\hat{\theta}^i)(\Delta y^i - H(x^i, u)\hat{\theta}^i))$$

and

$$M_{n+1}^{-1} = M_n^{-1} + H_n^T \hat{R}_n^{-1} H_n$$

The calculation procedure uses iterations through the data to arrive at a consistent optimal estimate. The estimate is then used to update the sensor variance and parameter uncertainty levels for the data record. Prior information, M_o, on the parameter accuracy is stored along with the estimates of the sensor noise level and the parameter estimates themselves.

The procedure is quite compatible with the processing scenario. If a maintenance action or sensor replacement has been performed between data records, the parameter covariance and sensor noise levels can be increased to make the filter respond to the new information. The parameter estimates and sensor noise levels are also used in the sensor diagnostic routines to determine the threshold levels to validate new sensor measurements.

3.6 TRENDING

The parameter estimation algorithm produces time-varying estimates of engine/component module health. It is desired to correlate these estimates with engine maintenance actions. However, since the module-directed rating parameter estimates are noisy estimates (i.e., not known with certainty) it is useful to to trend these estimates. This section describes the development of a trending algorithm.

The trending routine fits a piecewise linear function to data. The procedure is based on the assumption that an engine health parameter will decrease linearly over time until a maintenance action occurs. Ideally, at that point, the engine health parameter will increase to some value. The jump reflects the improved condition of the engine (or component module). Linear deterioration resumes until another maintenance action occurs, and the cycle is repeated. The routine attempts to find the linear trends and jump point(s) in the noisy data.

The general approach followed by this routine is to determine potential jump points using a minimum sum of squares criterion. The best jump points are then selected from the potential ones. Least-squares line segments are fitted between the selected jump points. The details of this approach will be described next.

The input to the algorithm is a set of N data points, denoted (x_i, y_i), $i=1,2,\ldots,N$. Normally, the x values will represent total operating time of the engine and the y values will represent an engine or module rating parameter. The first step is to sort the data so that $x_i \leq x_{i+1}$ for all i. Then the best single line is fitted to the data. This line can be written as $y=mx + b$.

Associated with this line is a sum of squares, $SS(0)$, defined by

$$SS(0) = \sum_{i=1}^{N} (\hat{y}_i - y_i)^2$$

(see Figure 3.16).

Next, two line segments are fit to the data to determine if there is a significant improvement in the total sum of squares. This is done by choosing a J between 1 and N, and then fitting line segments to the data from x_1 to x_J and another line segment from x_{J+1} to x_N (see Figure 3.17). As above, there is a total residual sum of squares associated with the line segments, and this total depends on J. J is varied from 2 to $N-2$, and J^* is set equal to the J which minimizes the total sum of squares (see Figure 3.18). This total is denoted $SS(1)$, the minimum sum of squares with one jump. This procedure, called FINDJUMP, forms the basis of the entire trending routine. FINDJUMP(I,J,K) returns in K the best jump point between x_I and x_J. On the first call to FINDJUMP, $J=1$, $J=N$ and the procedure returns with $K=J^*$.

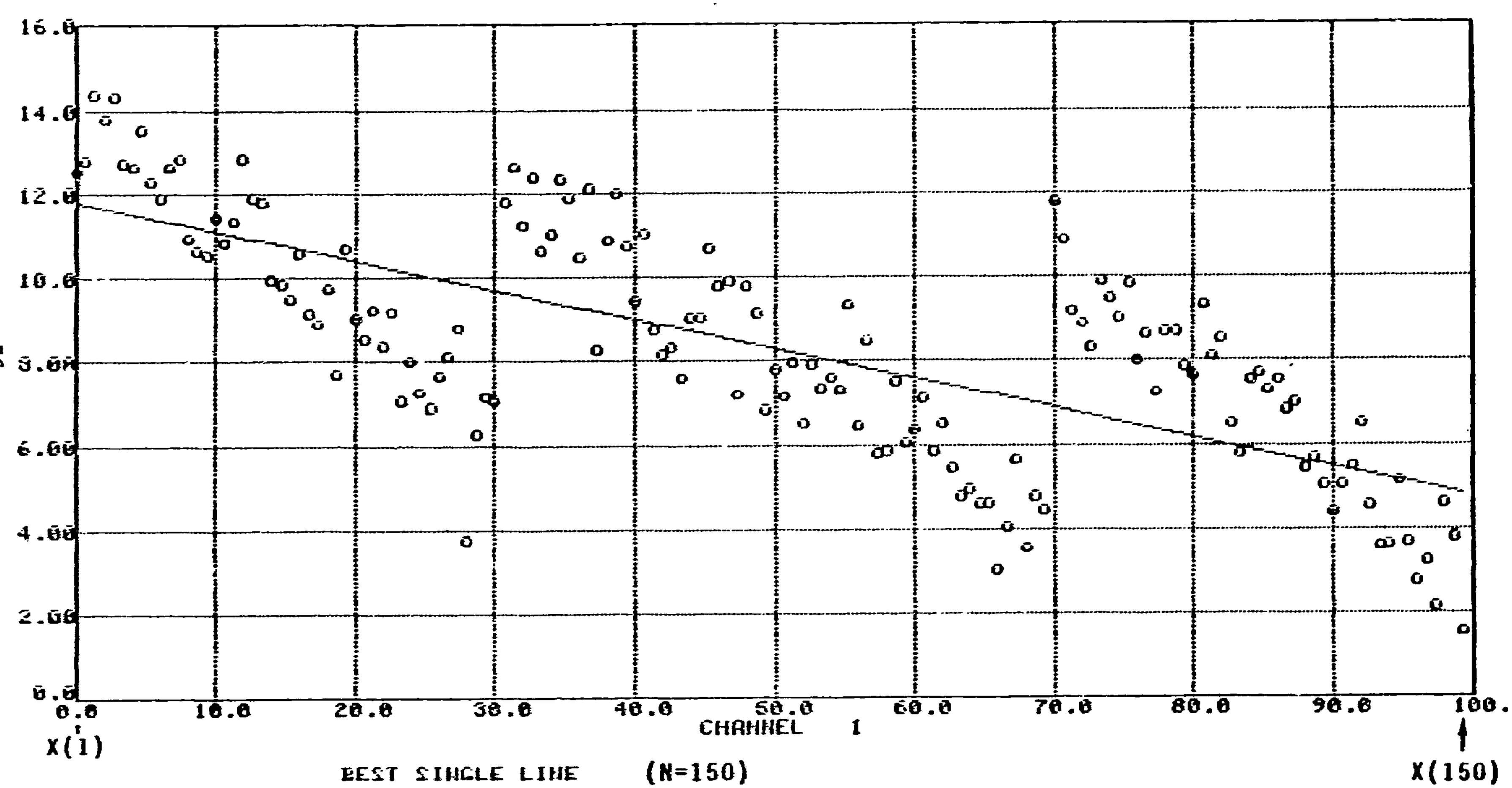


Figure 3.16 Trending Routine Example

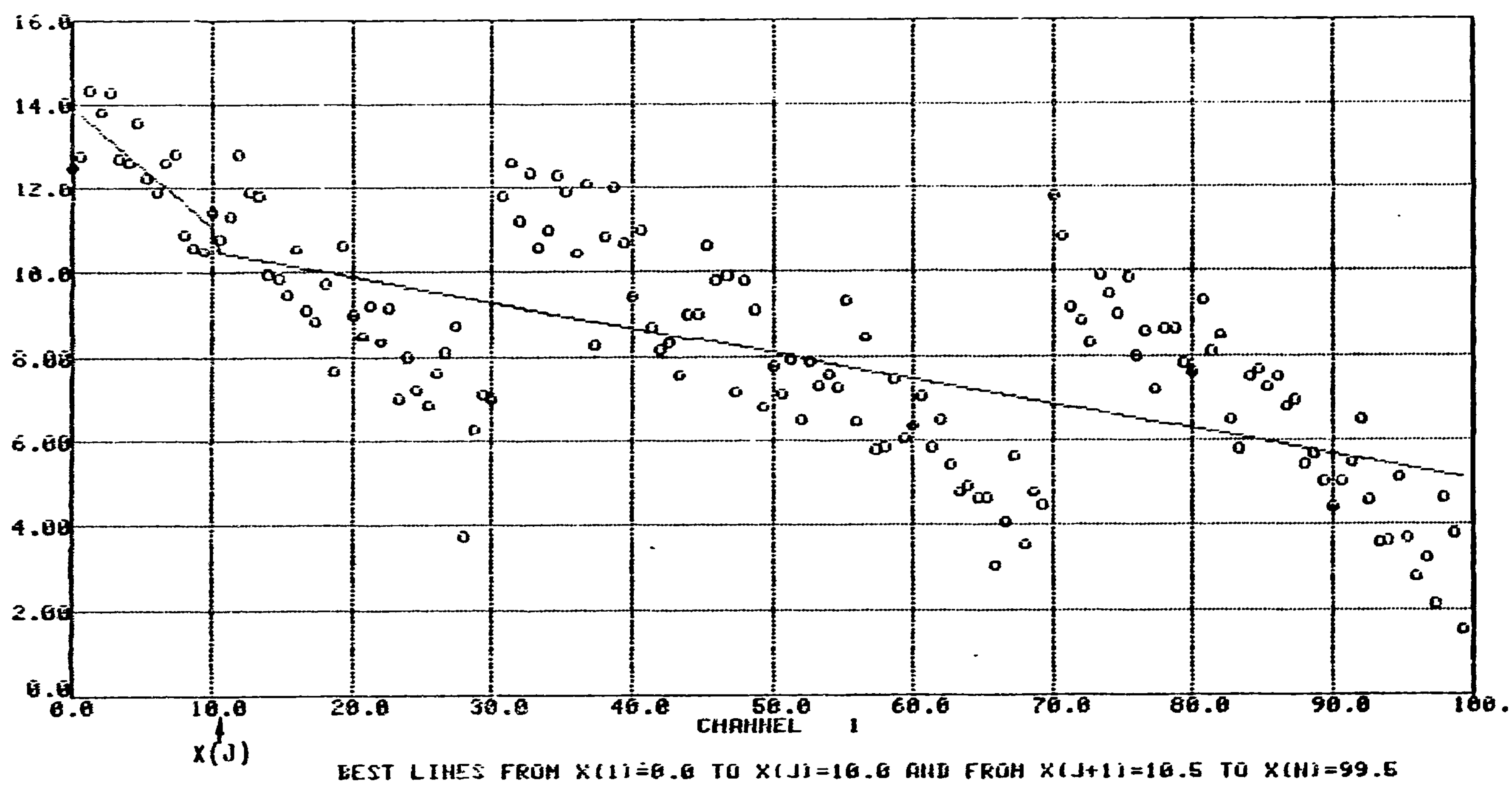


Figure 3.17 Trending Example

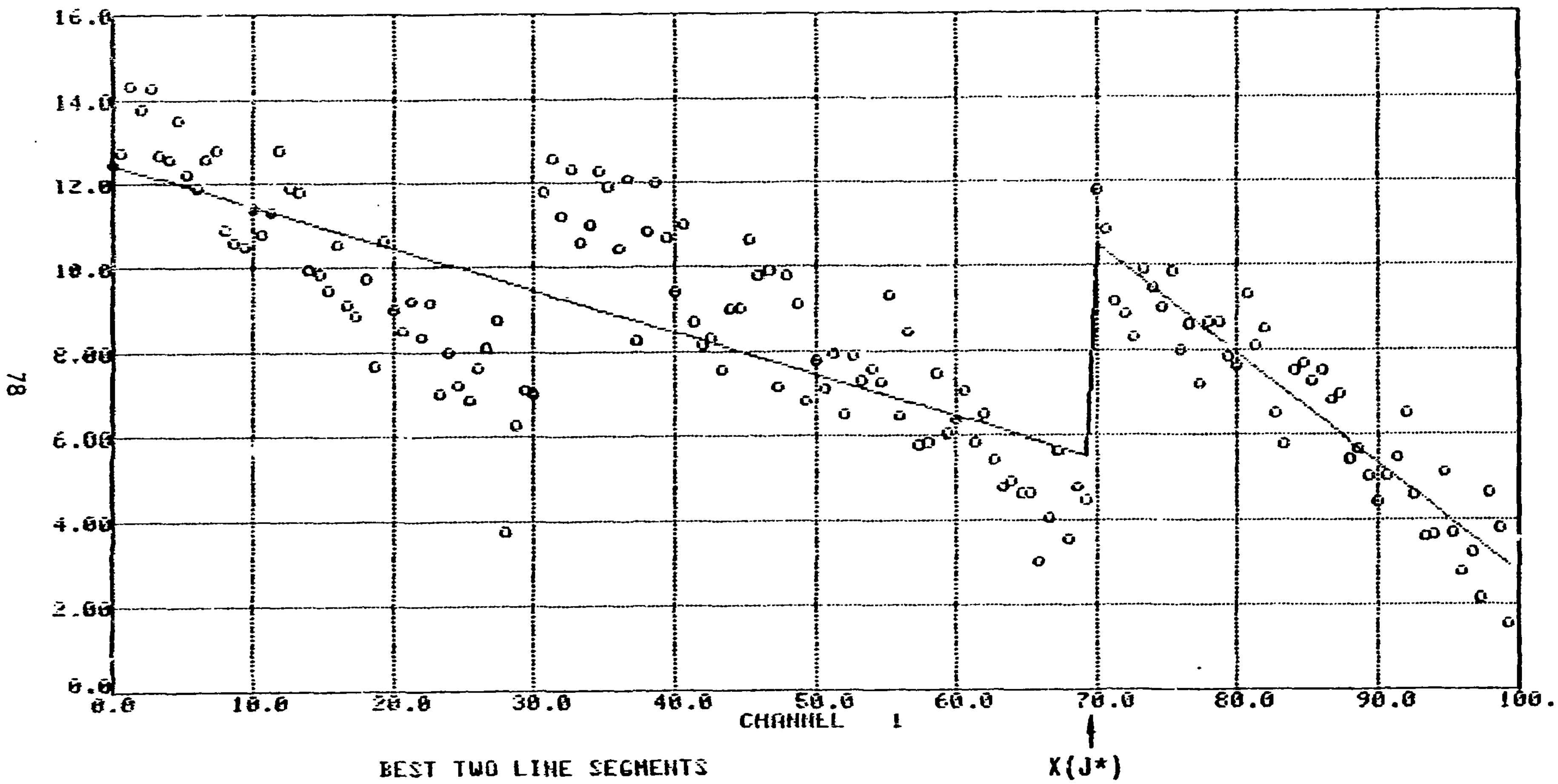


Figure 3.18 Trending Example

If $SS(1)$ is not significantly less than $SS(0)$, the trending routine returns the best single line and halts. Otherwise, $SS(2)$, the (near) optimal sum of squares with two jumps (three line segments), is computed. In order to compute $SS(2)$, it is necessary to determine the best two jump points, J_1^* and J_2^*. That is, the problem is to find J_1^* and J_2^* which minimize the following sum:

$$\min_{J_1 < J_2} \left\{ \sum_{i=1}^{J_1} (y_i - y_i^{(1)})^2 + \sum_{i=J_1+1}^{J_2} (y_i - y_i^{(2)})^2 + \sum_{i=J_2+1}^{N} (y_i - y_i^{(3)})^2 \right\} \tag{3.16}$$

where $y^{(1)}$ is the best line from x_1 to x_{J1}, $y^{(2)}$ is the best line from x_{J+1} to x_{J2}, etc. There are $N(N-1)/2$ possible choices of J_1 and J_2. For large N, enumerating all possibilities is a computationally tractable problem. Instead, up to 15 candidate jump points are determined. Then, all pairs of these are enumerated until the two are found which minimize Eq. (3.16).

The 15 (or less) candidate jump points are determined as follows. It is assumed that J^*, these best jump point between x_1 and x_N, has been determined. $C1=J^*$ is the first candidate. The second and third candidates are determined by the FINDJUMP routine; FINDJUMP (1, C1, C2), FINDJUMP (C1+1, N, C3) return two more candidates, C2 and C3. Similarly, the fourth candidate is determined from FINDJUMP (1, C2, C4), etc. (see Figure 3.19). Fewer than 15 candidates are determined if N is small. Only these candidates are searched for the best two jump ponts. These are denoted J_1^* and J_2^* (see Figure 3.20). Then, $SS(2)$ is the sum of square given in Eq. (3.16) for $J_1=J_1^*$ and $J_2=J_2^*$.

If $SS(2)$ is not significantly less than $SS(1)$, the trending routine returns the best two line segments (corresponding to the jump at J^*) and halts. Otherwise, $SS(3)$ is determined by considering all triples of jumps among the 15 candidates. Table 3.11 lists $SS(i)$, $i=0,1,2,3$ for the example

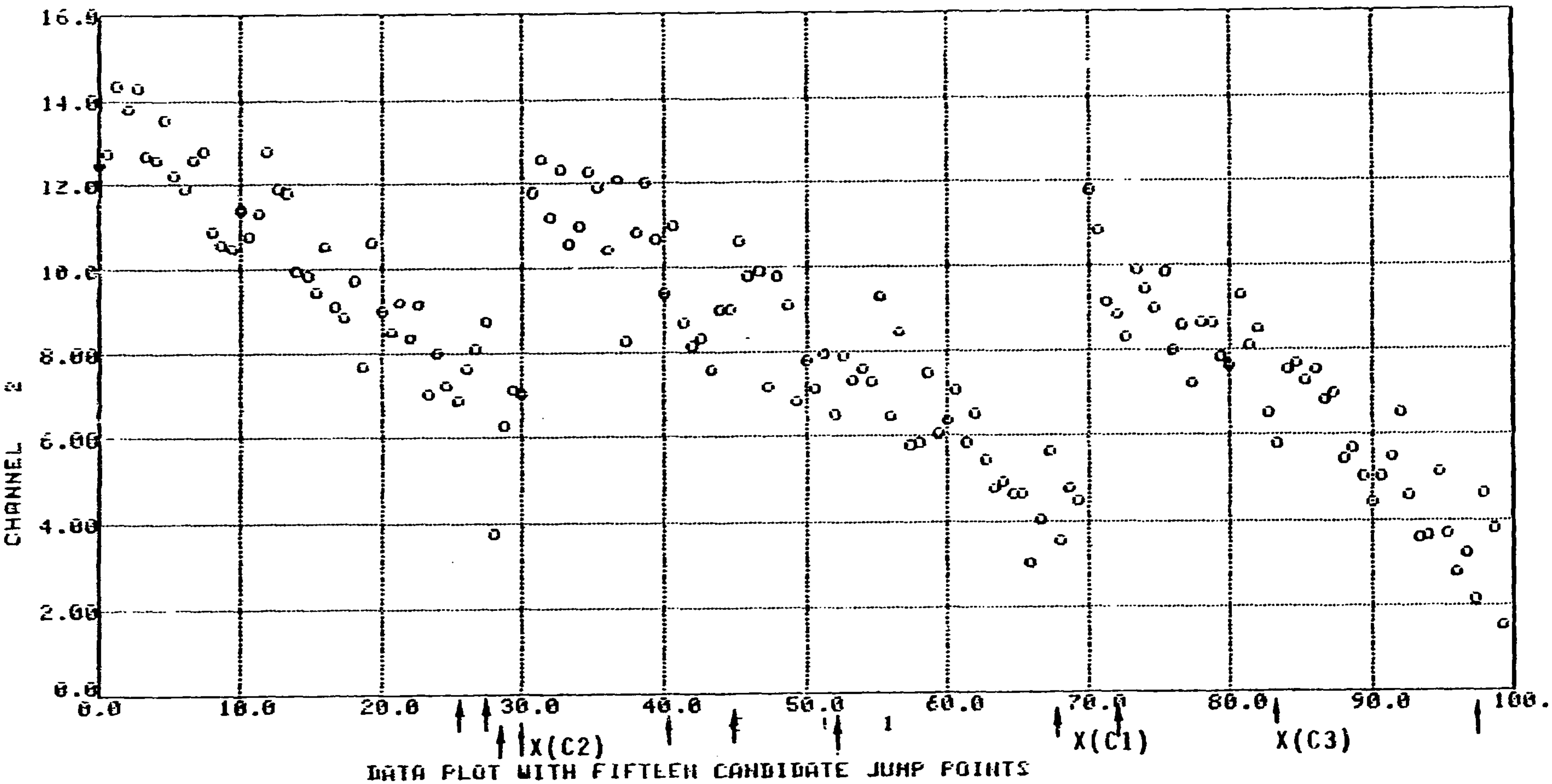


Figure 3.19 Trending Example

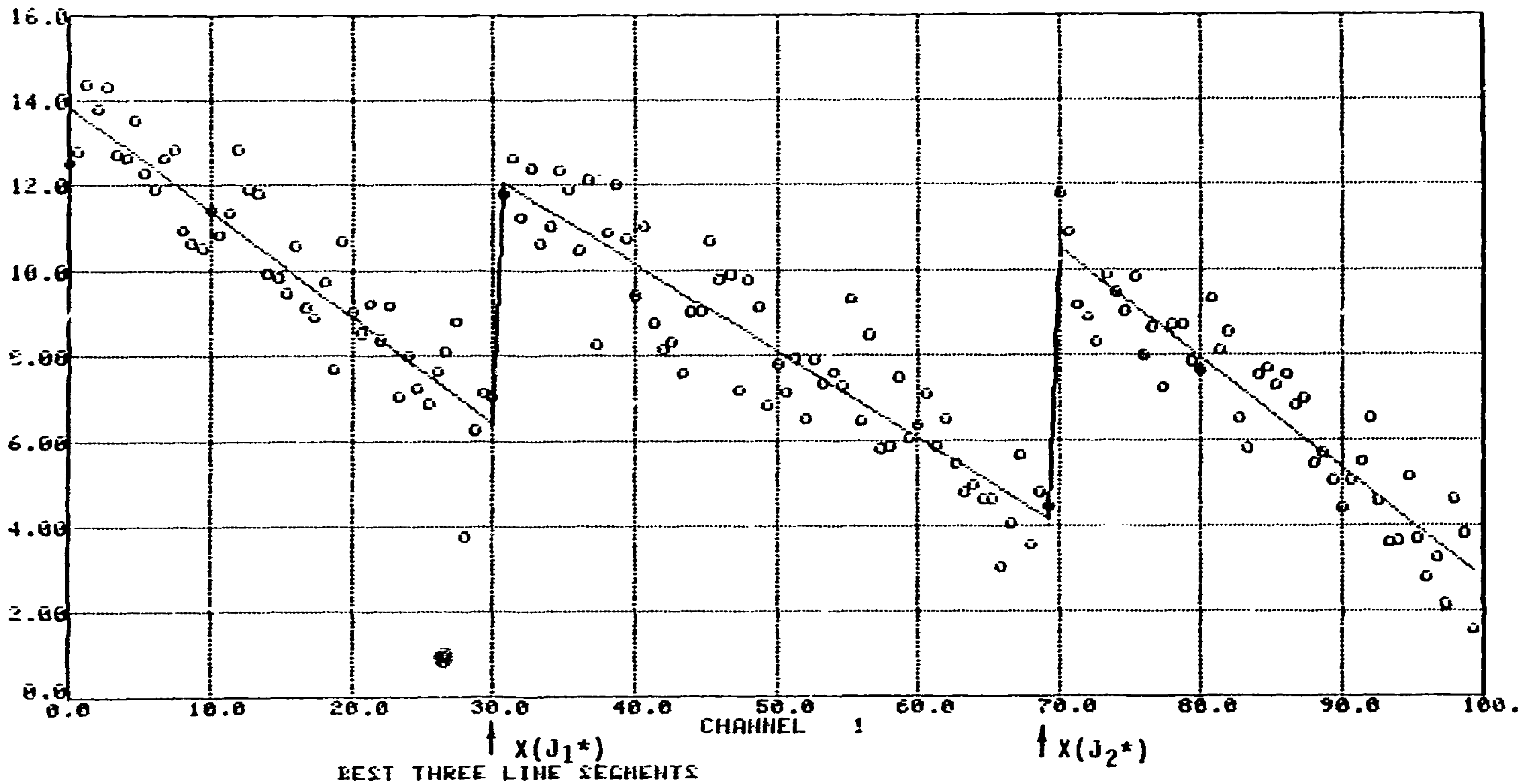


Figure 3.20 Trending Example

Table 3.11

Sum Of Squares In Example

I	SS(I)
0	553.14
1	348.53
2	134.03
3	124.15

N=150

Optimal number of jumps occur at I=2

shown in Figures 3.16 through 3.20. Figure 3.20 shows the final trending result.

The trending routine flowchart is summarized in Figure 3.21.

Gaps in the data do not present any difficulty to the trending routine (see Figure 3.22). It is also possible to specify in advance the number of jumps desired. For example, even if there are two jumps corresponding to engine maintenance actions, specifying no jumps will show if there is a long-term linear decline (as in Figure 3.16). Additional sample results are shown in Figures 3.23 through 3.25.

NJ = NUMBER OF JUMPS

MAXNJ = MAXIMUM NUMBER OF JUMPS (<15)

SS(I) = TOTAL SUM OF SQUARES WITH I JUMPS

THRSH = THRESHOLD VALUES (TYPICALLY THRSH = 0.75)

STEP 1. SORT THE DATA (BY x VALUES) NJ ← 0.

STEP 2. COMPUTE SS(0) AND BEST SINGLE LINE (NO JUMPS).

STEP 3. COMPUTE SS(1) AND BEST TWO-LINE SEGMENTS (1 JUMP).

STEP 4. IF SS(1)/SS(0) > THRSH, GO TO STEP 10.

STEP 5. DETERMINE UP TO 15 CANDIDATE JUMP POINTS.

STEP 6. NJ ← NJ+1. IF NJ > MAXNJ, GO TO STEP 10.

STEP 7. COMPUTE SS(NJ+1) AND BEST NJ+2 LINE SEGMENTS (NJ+1 JUMPS) FROM THE CANDIDATE JUMPS.

STEP 8. IF SS(NJ+1)/SS(NJ) > THRSH, GO TO STEP 10.

STEP 9. GO TO STEP 6.

STEP 10. OUTPUT BEST NJ+1 LINE SEGMENTS (NJ JUMPS). STOP.

Figure 3.21 Flowchart For The Trending Routine

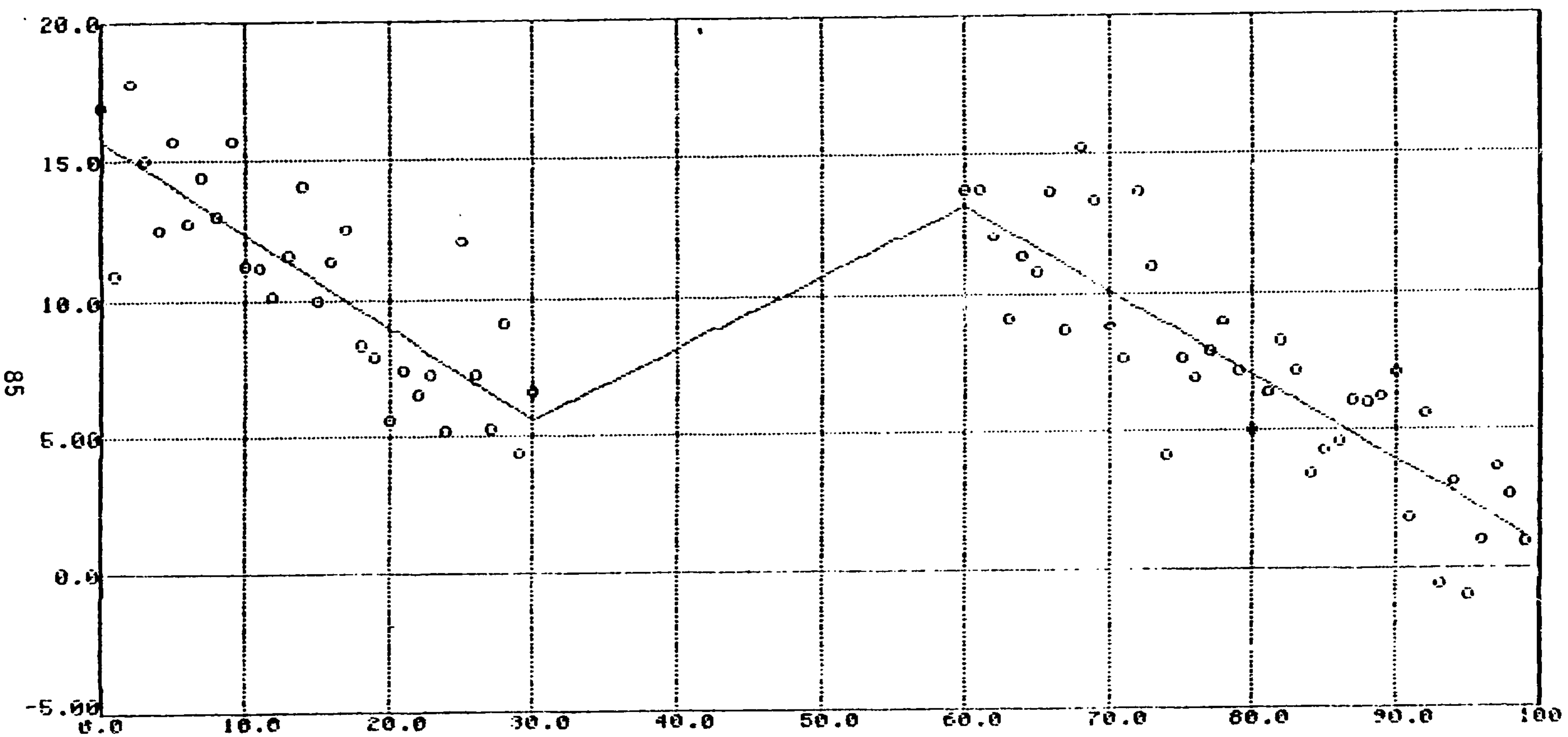


Figure 3.22 Sample Trending Routine Result: Data With A Gap in X Values

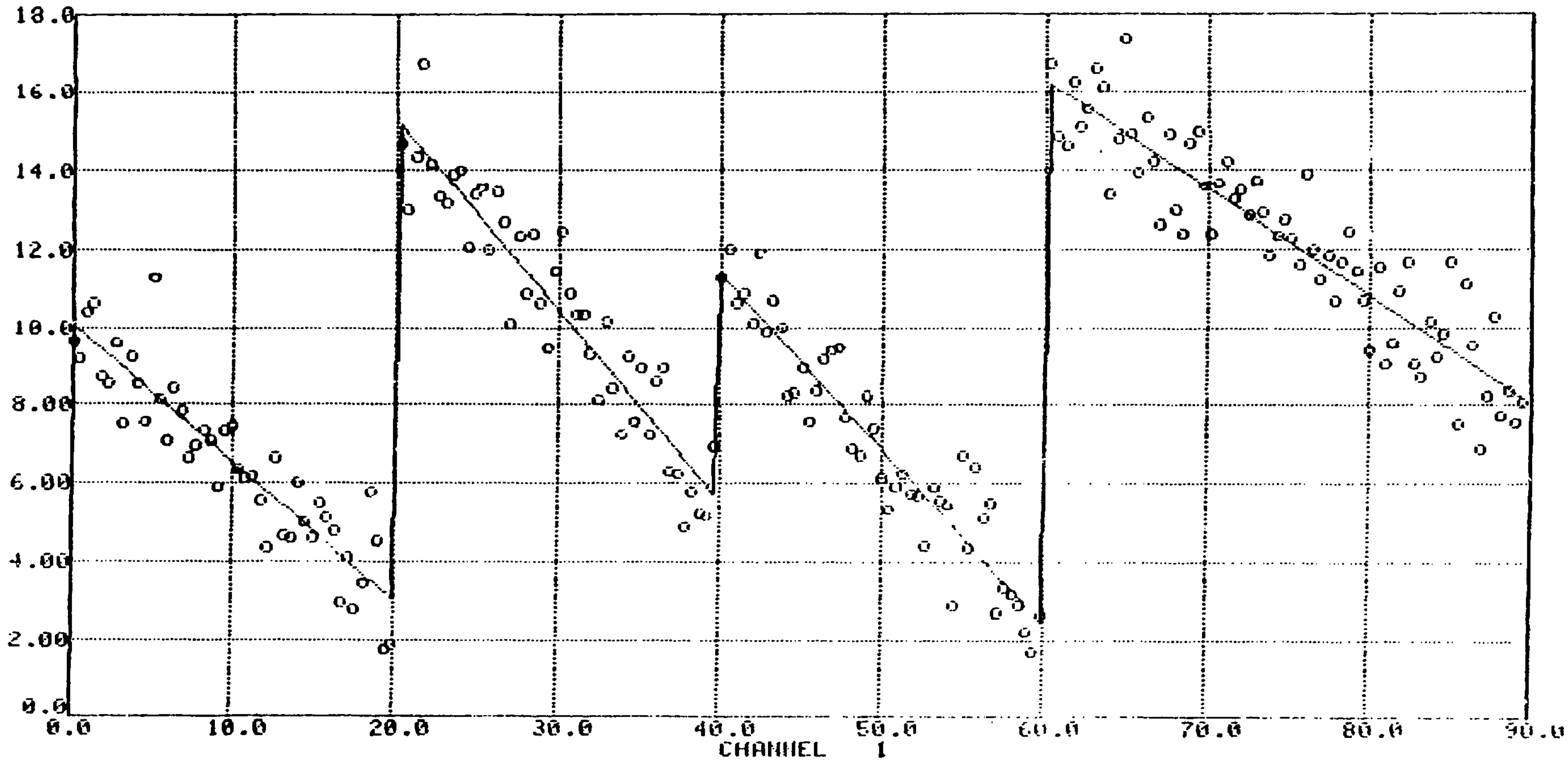


Figure 3.23 Sample Trending Routine Result: Data With Three Jumps

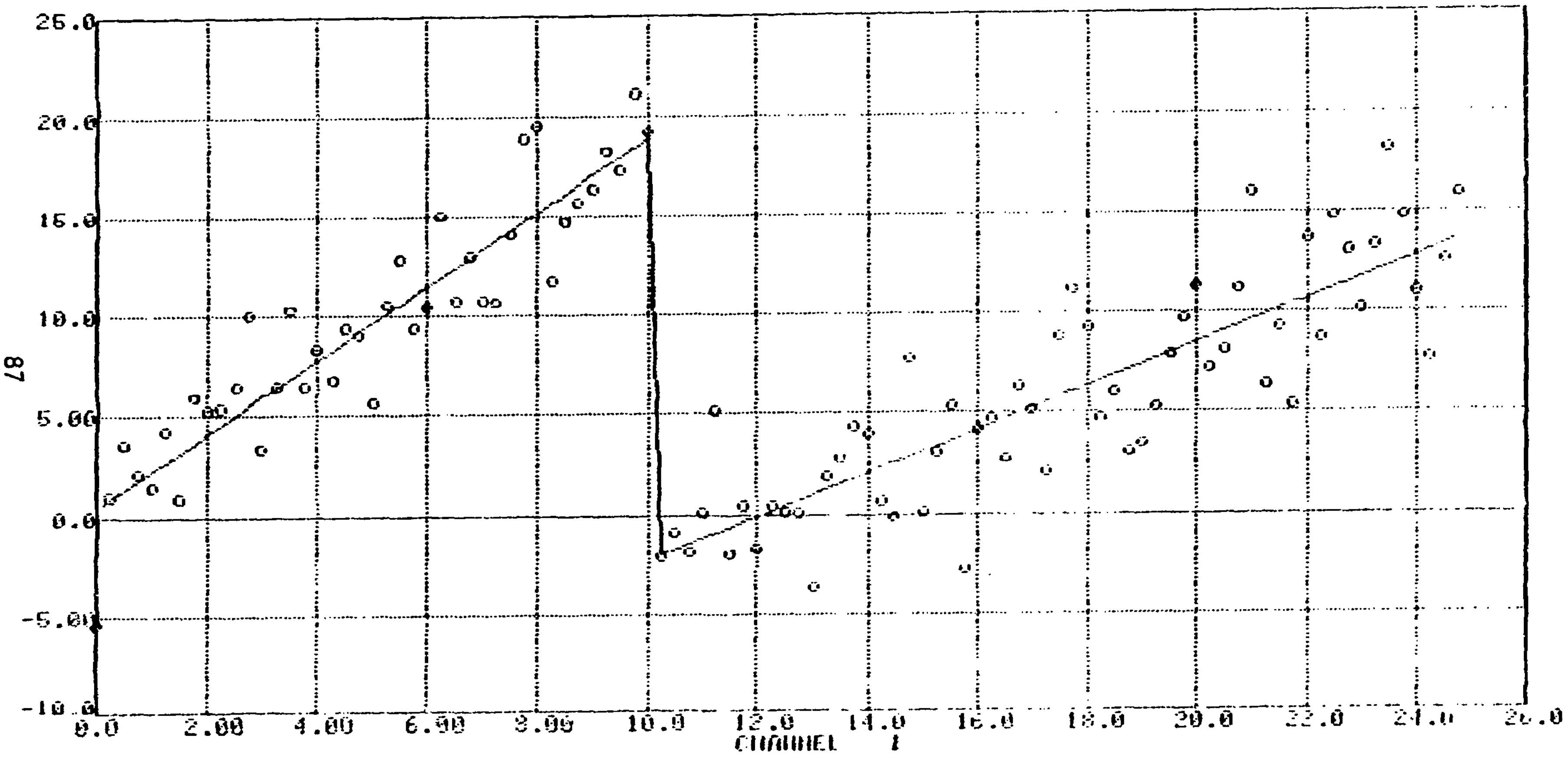


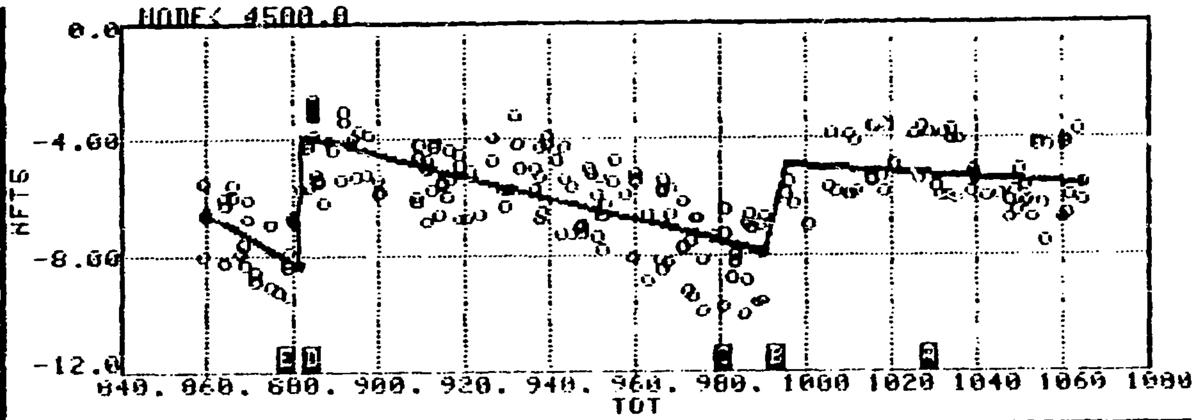
Figure 3.24 Sample Trending Result

ENGINE PROFILE
MYRTLE BEACH AFB

E5212
0536R

STATUS	FMC
PACER ITEM	3707/6800 C (HPT BLD)
NET GPA	100.0 %
TAT I	236
TAT II	194
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.6/ 6.0FFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	1064.6 HRS
CYCLES	3707 C (010L)

DIAGNOSTICS



MAINTENANCE HISTORY

B: 79250/1-F.O.M. REMOVAL OF FAN STATOR VANE.
ITEM REMOVED & REINSTALLED.
D: 79169/1 -ENGINE WATER WASH.

4 AUG
1981

Figure 3.25 Sample Trending Result

IV. INTEGRATION WITH MAINTENANCE MANAGEMENT

4.1 INTRODUCTION

The key to the effectiveness of an automated turbine engine monitoring system is its incorporation in the maintenance/ logistics framework of the Air Force. Chapter IV presents the requirements for integration of a generic TEMS with the Air Force maintenance environment. Requirements are outlined in terms of function and keyed to specific software capabilities. Background on the maintenance organization is provided and the maintenance management philosophy is discussed.

Motivating Factors for Automated Engine Monitoring

The factors which drive the need for and the structure of an integrated engine monitoring system are two-fold:

(1) minimization of operations and support costs of the Air Force engine inventory [30]; and

(2) maximization of the availability of engines to support Air Force peacetime force capability and/or wartime operations [31,32].

While these requirements have always been recognized by military and civilian organizations, it is within the past two decades that the complexity of meeting these needs has been most urgently realized. The events which have most recently affected this realization are:

- introduction of increasingly more complex engine designs (for higher performance aircraft) into the inventory [31]
- increasing rate of growth of the inventory as older engines (J79, TF41, TF30) are retained, and large numbers of the new engines supporting advanced aircraft (A-10, F-15, F-16) are produced in large quantity [33]
- rising costs of operation and support, in both personnel and material [30]

The Air Force is responding to these events in several ways:

- introduction of new maintenance concepts [34,35]
- development and evaluation of two new engine monitoring systems
- implementation of a comprehensive engine management system to support both home base and global operations [33,36].

Figure 4.1 illustrates the primary motivational elements for integrated engine monitoring capability.

4.2 REQUIREMENTS BACKGROUND

4.2.1 Management Organization

The Air Force engine management structure consists of three levels: base, depot, and command. Figure 4.2 illustrates the management organization.

The first level is the operating base. It consists of the flight line and the Jet Engine Intermediate Maintenance (JEIM) facility. The Tactical Air Command (TAC), which was the primary focus of this study, operates under a production-oriented maintenance organization (POMO). This base management structure differs from the other commands in that various propulsion specialists have been removed from the shop and assigned to the flight line, allowing for a more flexible utilization of manpower.

Under the POMO, the flight line is manned by members of the Aircraft Generation Squadron (AGS). The primary mission of the AGS is to support a wing's aircraft sortie schedule. They support installed engine maintenance. The Component Repair Squadron (CRS) operate the JEIM facility and perform the uninstalled engine repair. Base-level personnel are responsible for specifying engine trim requirements, diagnosing faults, directing engine removals, and troubleshooting engine discrepancies. Based on factors such as type and extent of failure, estimated repair time, ability to isolate failure source accurately, and local availability of resources, the decision is made to perform flight line maintenance on line replaceable units (LRU level), JEIM repair, or transport the engine (or modules/subassemblies) to a centralized depot [37,38].

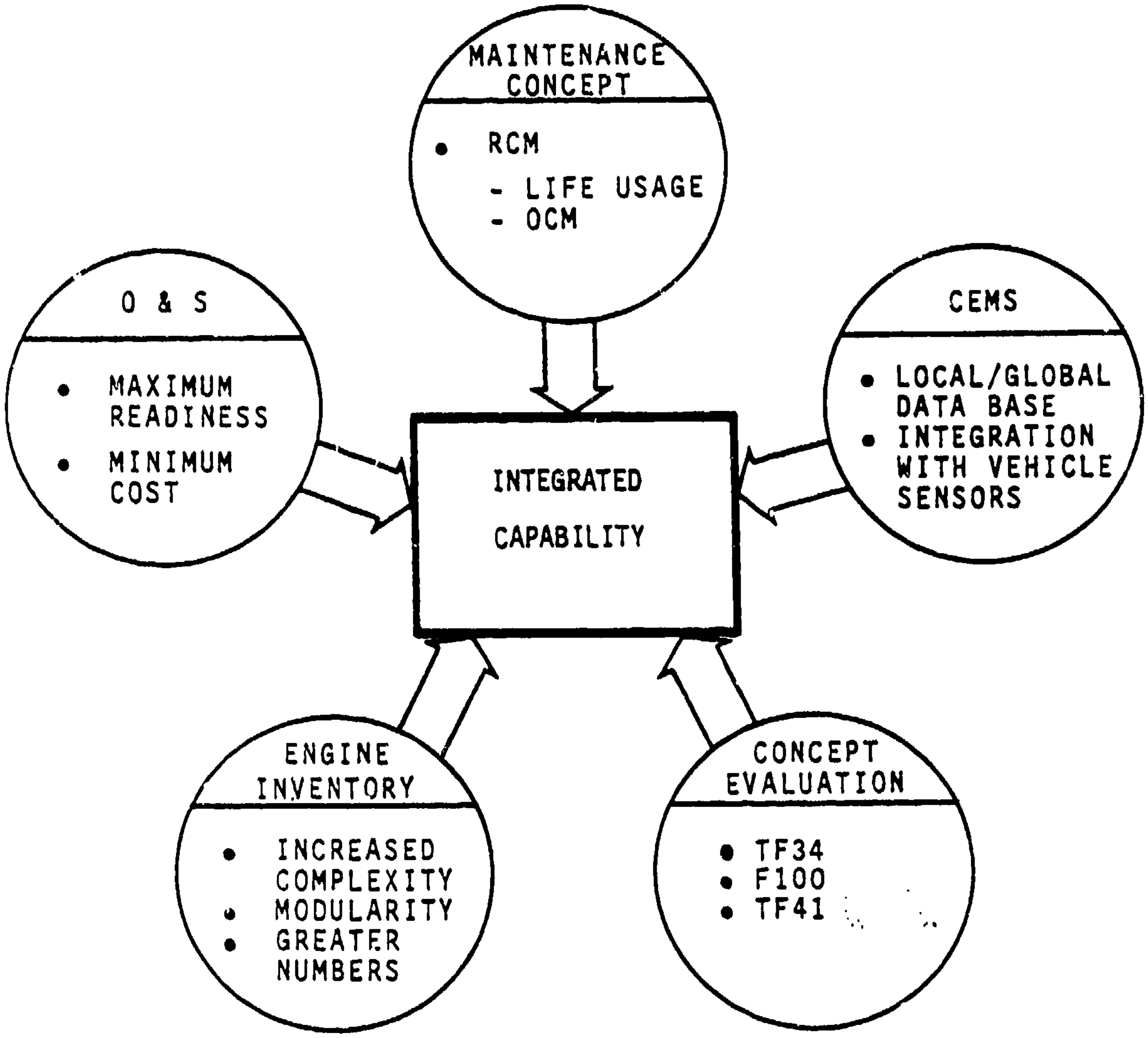


Figure 4.1 Driving Elements for the Development of an Integrated Engine Monitoring Capability

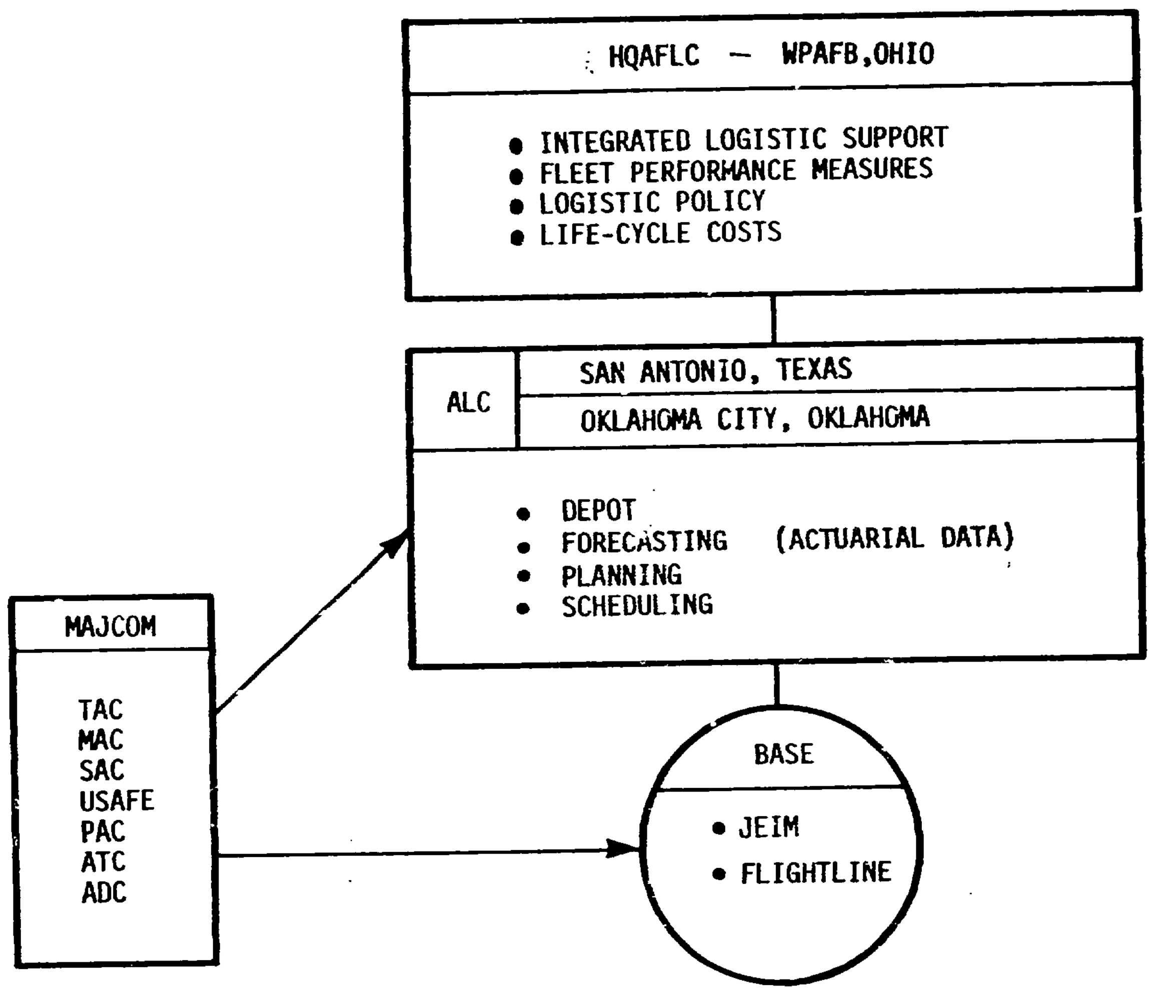


Figure 4.2 Air Force Engine Management Echelon

The Air Logistics Center (ALC), the second echelon, operates centralized depots for major repair. A team at each ALC is responsible for specifying the most economical level of repair necessary to return engines and modules to serviceable condition. Individuals assigned to an engine type monitor overall fleet health and process historical data to forecast failures and schedule removals over a two-year period. They use this actuarial data to predict workloads, spare parts procurement, and to calculate stockage objectives for both depot and base supply. Maintenance engineering staff at the ALC are responsible for anticipating and identifying maintenance problems. Based on their analysis, they recommend alternative approaches and procedures for engine operation and support [37].

The third level of the engine management structure, the Headquarters Air Force Logistics Command (HQAFLC), is responsible for establishing policy for inventory control and maintenance procedures. They develop the software and mathematical models used throughout the Air Force to perform logistical analyses and support.

In addition to the line maintenance and logistics organization described above, the operational commands provide parallel management organization. The engine managers located at each of the major commands (MAJCOM) are concerned with monitoring fleet performance. They determine mission capability and readiness posture of each base and the overall fleet in their respective command. Like their counterparts at the ALC's, MAJCOM managers also participate in the prediction of workloads, spare parts procurement, and the calculation of stockage objectives [38,39].

A comprehensive engine management system currently under development is evidence of the Air Force's commitment to improved engine management within a structured organizational framework. The proposed system will link various users in the Air Force engine maintenance/logistics process (see Figure 4.3).

4.2.2 Engine Maintenance Philosophy

Air Force engine maintenance policy for the 1980s has been defined using the principles of reliability centered maintenance (RCM). RCM stemmed from a need to define an effective strategy for minimizing aircraft and engine

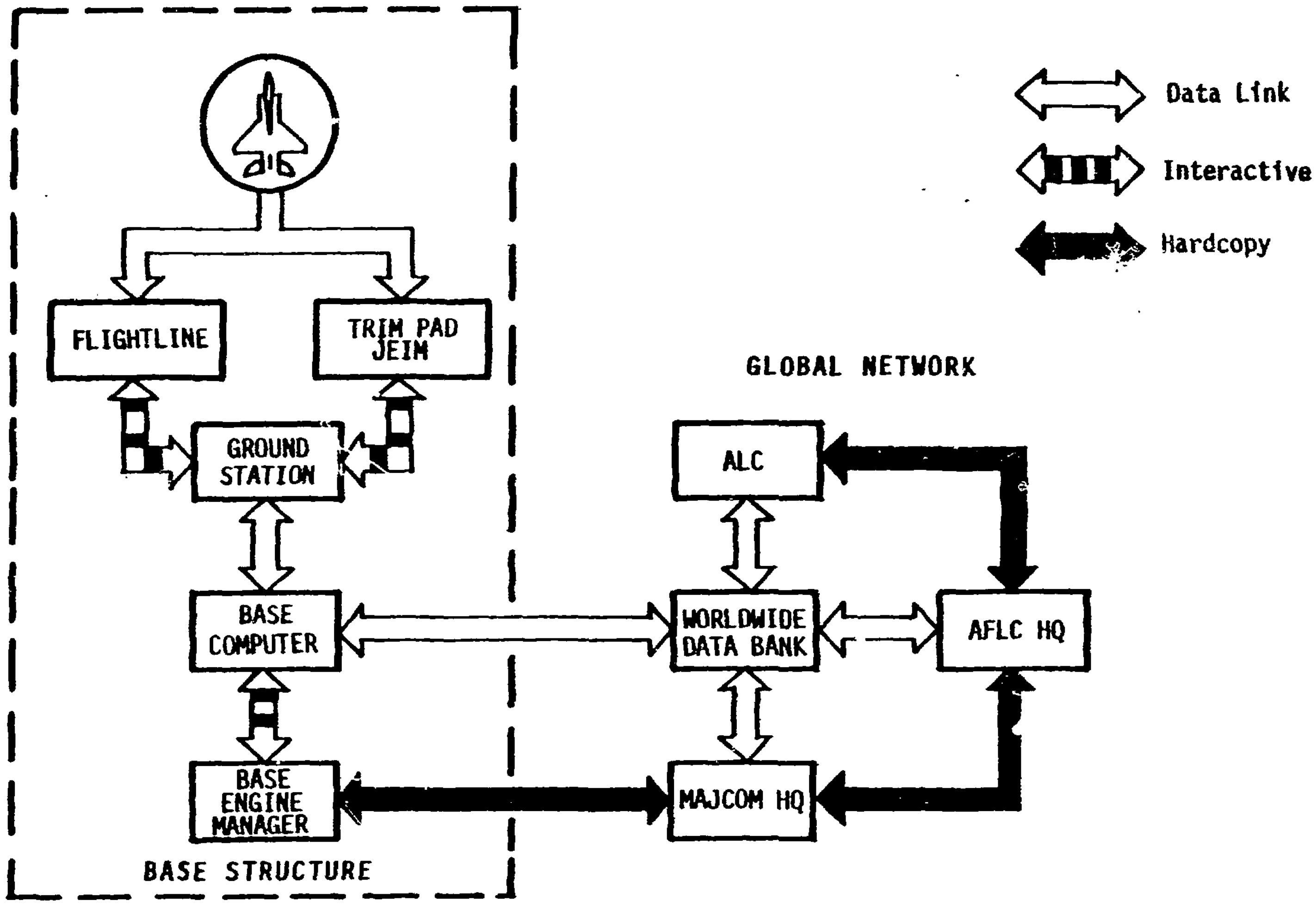


Figure 4.3 Integrated Maintenance/Logistics Network

operation and support (O&S) costs. Its objective is the specification of a maintenance program that "achieves inherent safety and reliability capabilities at minimum cost" [34].

The adoption of modular engine design impacts engine operation and support. New engines consist of several modules and minor external accessories (e.g. casing, wiring, plumbing, etc.), which can be easily removed from the engine for maintenance. With an adequate local inventory of spare modules, this procedure can minimize engine down time and improve availability. The successful exploitation of modular maintenance requires the ability to isolate engine faults to the modular level [31,32].

Sophisticated new engine design has, therefore, imposed requirements on maintenance procedures to:

- acquire and apply diagnostic indicators to support more complex design
- monitor life usage on a module/component rather than an engine basis
- enhance fault detection and isolation capability to the module level at the flight line as well as the intermediate and depot levels.

The concept of an MOT for an entire engine has been replaced by hard time limits for critical engine components whose failure modes are characterized by low-cycle fatigue, thermal fatigue, or stress rupture. RCM requires the collection of accurate life usage data for all hard time components so that engine removals can be scheduled. The monitoring of equivalent age (i.e. operating time, LCF counts, or time at or above certain temperature levels) is a formidable data collection and documentation task because an engine can typically have upwards of 100 life-limited components [34].

The major objective of RCM is to eliminate the process of complete equipment overhaul. Under the previous overhaul concept, at a set operating age an engine was removed and transferred to a depot facility for complete teardown, inspection, component replacement/refurbishment, and reassembly in accordance with standard technical orders. When the engine was returned to service, the operating age was reset to zero on the assumption that the overhaul had returned the engine to a state comparable to its original condition. Not only is this expensive, but there is evidence that some engine failure phenomenon are not directly age related across the entire engine population.

RCM is actually a planning process that identifies the "best" (i.e. cost-effective, safety-oriented) maintenance procedure for a unit, its major subassemblies, and components. The exact specification of maintenance is based on engine condition and is called on-condition maintenance (OCM). The procedure specification is dependent on the unit's failure modes and characteristics. RCM categorizes failure modes based on an ability to identify incipient failure. It is desirable although not always feasible to identify a reduced resistance to failure. For these failure modes, it is advisable to identify life usage limits that either direct component replacement or establish fixed interval periodic maintenance. Figure 4.4 is a flow diagram depicting the development of an RCM maintenance plan.

For those engine failure modes that can be classified by condition monitoring, it is necessary to establish installed engine inspection procedures (e.g. borescope) and monitoring techniques (e.g. oil analysis, performance trending) to identify incipient failures in a timely manner. Turbine engine monitoring systems are obviously an important source of both condition data (diagnostics, performance) and usage factors (time, cycle, temperature time factors) [40].

Visual borescope inspection and oil analyses are an effective means of gathering a small portion of the engine condition information. These techniques are inadequate, however, for providing extensive fault isolation capabilities, diagnostics, or performance trending. Development of an automated monitoring capability appears to be necessary if RCM concepts are to be successfully and cost-effectively applied to Air Force engine support. The next section examines the management decisions associated with RCM and identifies the types of information required at each user level in the engine operation and support cycle.

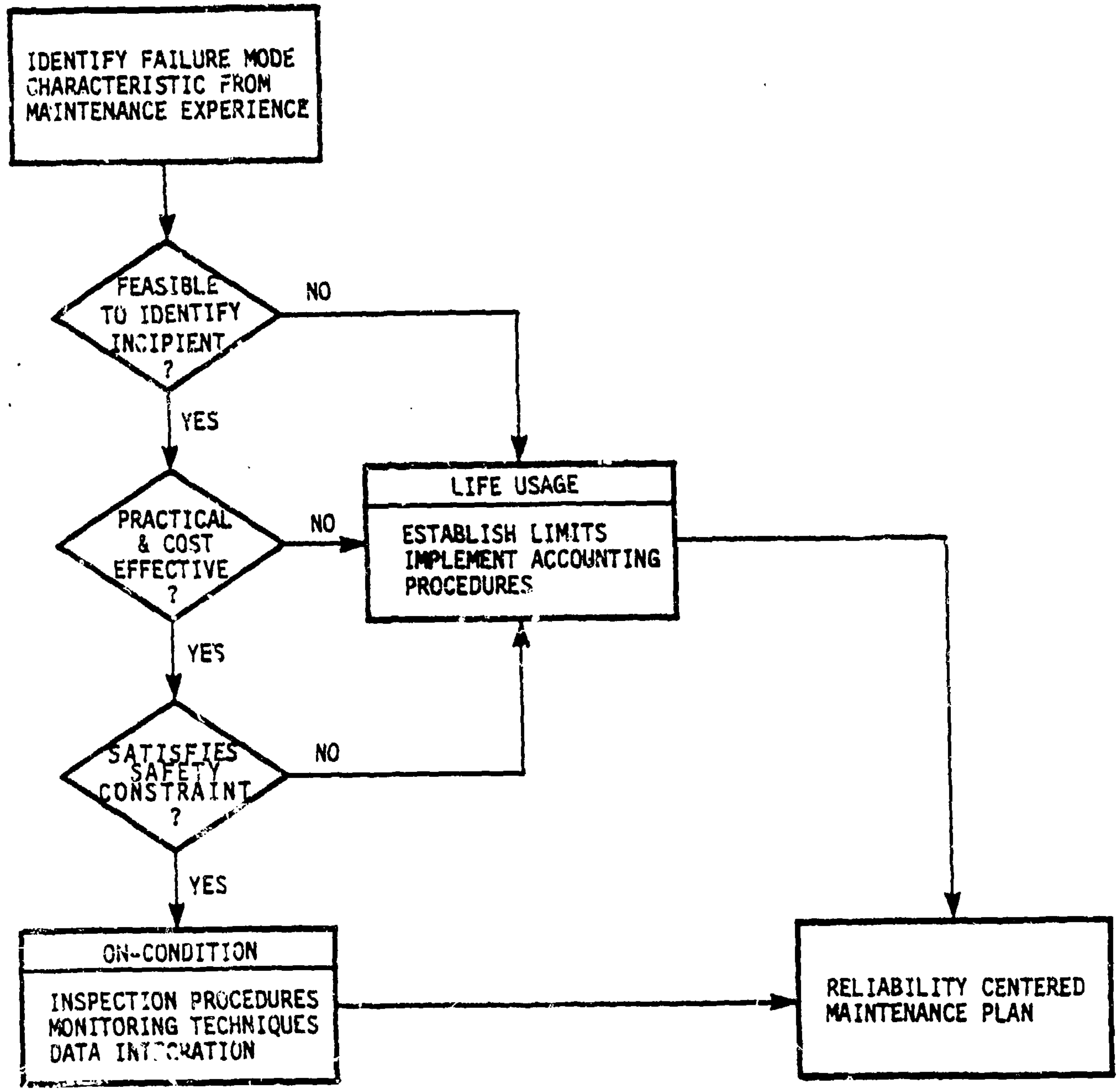


Figure 4.4 Development Process For An RCM Plan

4.2.3 User Requirements for Monitored Propulsion Data

The user requirements for engine monitoring data are dependent upon the management decisions implemented at each engine support level. The user categories are:

- pilot/flight crew
- flight line (AGS)
- JEIM (CRS)
- depot
- command

These users with their respective information requirements determine the data acquisition and processing requirements, software logic, and information access capability.

The cockpit level scenarios associated with engine support are limited to decisions related to mission abort and pilot/crew safety. These decisions require in-flight information that alert the pilot of a critical event (e.g. overtemp, overspeed) that may impact an in-flight decision. To be effective, the alerts must be displayed on-exception and restricted to only those that specifically require the pilot to take an action. Pilot/flight crew reported discrepancies or squawks have been valuable indicators of maintenance requirements (e.g. out-of-trim, stall, flameout). Instrumenting the cockpit with a record option facilitates the collection of suspect diagnostic data that are used in conjunction with the pilot's debriefing report.

Maintenance level scenarios span three user groups: flight line, JEIM, and depot. Table 4.1 classifies some typical engine maintenance decisions by base management level. At the flight line, the AGS must make rapid go/no-go decisions for maximum sortie capability. The detection of engine faults, isolation to the LRU level, and the specification for a maintenance action are important flight line diagnostic decisions. Because the trim pad is operated by flight line personnel, trim decisions and procedures occur primarily at this level.

After engine removal, the JEIM controls the asset. In practice, both flight line and shop managers participate in the removal decision. Detection and isolation decisions are supported by test cell troubleshooting. The

Table 4.1

Typical Maintenance Decisions/Scenarios By User Level

	FLIGHT LINE	JEIM	DEPOT
GO/NO-GO	X		
TRIM	X		
FAULT DETECTION	X	X	
REMOVAL	X	X	
LRU ISOLATION	X		
FAULT ISOLATION (MODULAR LEVEL)		X	X
MAINTENANCE SPECIFICATION	X	X	X
TREND MONITOR		X	
NEAR-TERM FORECAST		X	
DEPLOYABLE ENGINE STATUS	X	X	

Table 4.2

Troubleshooting Information Requirements

	INFORMATION REQUIREMENT					
TROUBLESHOOTING CAPABILITY	ENGINE HEALTH INDICES	DIAGNOSTICS	MAINTENANCE HISTORY	TEST STAND RESULTS	BASE CAPABILITY	RESOURCE AVAILABILITY
FAULT DETECTION	X	X				
FAULT ISOLATION	X	X	X	X		
SECONDARY DAMAGE IDENTIFICATION		X		X		
MAINTENANCE ACTION DETERMINATION				X	X	X

Table 4.3

Preventive Maintenance Information Requirements

	INFORMATION REQUIREMENT								
MAINTENANCE ACTION	ENGINE HEALTH INDICES	TIME FACTORS	CYCLE COUNTS	PILOT SQUAWKS	ALARMS (OLD AND NEW)	SOAP	HISTORY	HOT SECTION TIME (I,II)	VIBS
HOT SECTION INSPECTION	X			X	X			X	
ENGINE TRIM				X	X				
SENSOR FAILURE					X				
T.O. LIMITS	X				X	X		X	X
PERFORMANCE MONITORING	X	X	X		X	X		X	X
OCM SPECIFICATION		X	X		X		X		X

maintenance decision is dependent on these results, historical data, and local resources. Maintenance requirements associated with monitored trends would be identified at the JEIM level. The decision to remove the engine or perform LRU repair overlaps both maintenance levels at the base. Information requirements for troubleshooting and for preventive maintenance performed at this level are shown in Tables 4.2 and 4.3 [38,41].

Under RCM, an engine or module is transported to the depot level if the base cannot isolate the fault, the repair is beyond local capability, or technical orders specify the return. Depot level maintenance decisions are currently made by an OCM team that relies on historical data, removal justification, and engine/module records [37].

Engine logistics management decisions are centered at the depot and command level (see Table 4.4). At the depot, the users can be divided into two categories, maintenance engineering and actuarial support. Engineering staff is involved in the development of improved maintenance support for their assigned engines. This requires the monitoring of fleetwide engine health on a type/model basis. They also provide expertise in the identification of reliability and maintainability problems that must be addressed by component improvements. Actuarial staff are involved in the synthesis and analysis of engine removal data and failure statistics to determine the procurement of spares and the optimal distribution across the operating bases [42].

Command level engine management at the major commands and AFLC are concerned with a wide variety of operating problems in the engine support process. These range from determining the impact of the implementation of a Component Improvement Program to the development of logistics support models. To address the implications of these scenarios adequately, engine managers and logistics analysts must have access to certain types of engine performance and maintenance data on a fleetwide basis (see Table 4.5) [38].

4.3 FUNCTIONAL DESCRIPTIONS VS. REQUIREMENTS DEFINITION

Data products and information displays are driven by operational functions that must be implemented during the development of an integrated monitoring system. Design issues include:

Table 4.4

Logistics Management Decision Scenarios At Depot and Command Level

	DEPOT		COMMAND
DECISION TYPE	MAINTENANCE ENGINEERING	ACTUARIAL	(MAJCOM AND AFLC)
COMPONENT IMPROVEMENT PROGRAM (CIP) SUPPORT	X		X
CIP IMPACT			X
SPARE PROCUREMENT AND DISTRIBUTION		X	X
FLEETWIDE READINESS			X
MISSION PERFORMANCE ASSESSMENT	X		X
LOGISTICS SUPPORT MODELING			X
DEVELOPMENT OF IMPROVED MAINTENANCE SUPPORT	X		X

Table 4.5

Information To Support Typical Command Level Engine Management

DECISION TYPE	ENGINE REMOVAL/ FAILURE DATA	SELECTIVE MAINTENANCE RECORDS	BASE REPAIR RATE	FLEETWIDE STATUS	GROSS HEALTH TREND	MISSION SCENARIOS
COMPONENT IMPROVEMENT PROGRAM (CIP) SUPPORT	X	X			X	
CIP IMPACT			X	X		
SPARE PROCUREMENT AND DISTRIBUTION	X		X		X	
FLEETWIDE READINESS	X		X	X	X	X
MISSION PERFORMANCE ASSESSMENT					X	X
LOGISTICS SUPPORT MODELING	X		X	X	X	
DEVELOPMENT OF IMPROVED MAINTENANCE SUPPORT	X	X				

(1) data items;
(2) data format;
(3) access/inquiry;
(4) storage/archive;
(5) software logic; and
(6) interfaces.

Data items are derived from subsystems (e.g., TEMS, SOAP, MDCS). The formation of displays requires software logic (e.g., diagnostics, trending, etc.) to translate subsystem data to readily accessed management information.

Integrated requirements are based on the functional capabilities of the monitoring and management system. Table 4.6 illustrates how the important elements of the functional description impact key requirements for data acquisition/ interface, software, and hardware implementation. The data items identified during the survey analysis lead to development of the data acquisition and interface requirements. These are most important at the base level where the TEMS data (and most other data) originates. System operating functions defined by data acquisition and interface definitions drive the software logic definition and processing hardware configuration. Specific requirement definitions are presented in subsequent sections.

4.4 DATA ITEM INTERFACE RECOMMENDATION

Required data items established during the Phase I survey are listed in Table 4.7. This information is required by base personnel to perform maintenance functions. The data source for each is shown with the corresponding Air Force procedure. It should be pointed out that several items exist in hard copy <u>or</u> in the base computer, or both depending on the base implementation. It is assumed that these items will become resident within the integrated base level system. The data items are grouped by source subsystem in Table 4.8. Each subsystem and interface requirement is described in more detail below.

Table 4.6

Relationship Between Functional Definition and System Requirements

FUNCTION \ REQUIREMENT	DATA ACQUISITION/ INTEGRATION				SOFTWARE				HARDWARE				
	ACCURACY	STORAGE	PRE-PROCESSING	INTERFACE	MIS ARCHITECTURE	OPERATING SYSTEM	APPLICATION SOFTWARE	I/O DISPLAYS	AIRBORNE EQUIPMENT	TRANSFER DEVICE	SYSTEM INTERFACE	LOCAL PROCESSOR	INFORMATION NETWORK
DATA/INFORMATION:													
PERFORMANCE	X	X	X		X				X				
USAGE	X	X	X		X				X				
VIBRATION	X	X	X		X				X				
SUPPLEMENTARY DATA		X	X	X	X					X	X		
FUNCTIONS/LOGIC:													
DIAGNOSTICS	X				X		X			X			
TRENDING/GPA	X				X		X	X	X			X	
LIFE USAGE					X		X	X	X			X	X
VIBRATION	X				X		X	X	X			X	X
SUPPLEMENTARY					X		X	X	X			X	X
FORECASTING							X	X			X	X	X
INQUIRY LOGIC					X	X	X	X				X	X
DATA MANAGER					X	X						X	X
DISPLAY LOGIC					X	X	X	X				X	X

Table 4.7

Survey-Determined Required Data Items (Source/Documentation)

DATA ITEM	SOURCE	PROCEDURE REFERENCE	COMMENT
PERFORMANCE	TEMS	NONE	DEPENDENENT ON ENGINE AND LEVEL OF TEMS IMPLEMENTATION
TIME/CYCLES	TEMS EHR/ETTR	NONE T.O.-00-20-5-1 AFTO 93/AFTO 25	PROCEDURES DEVELOPED FOR EACH SYSTEM LEVEL I TEMS DATA SOURCE
VIBRATION	TEMS GROUND RUN	NONE ENGINE T.O.	IN-FLIGHT EVENT AND GROUND RUN
SOAP	HARD COPY OR HARD BASE	T.O.42B-1-9 (PROCEDURE) T.O.33-1-37 (MANUAL)	IMPLEMENTATION CURRENTLY DEPENDENT ON BASE PROCEDURE
BORESCOPE	ENGINE LOG	T.O.-00-20-5-1 AFTO 95	LOCATION OF LOG: - INSTALLED - DCM OFFICE - SHOP - JEIM OFFICE - DEPOT - DEPOT OFFICE
MAINTENANCE HISTORY	ENGINE LOG BASE COMPUTER MDCS	T.O.-00-20-5-1/AFTO 95 AFM 66-267 (DSD:G001)/AFTO 349	SEE BORESCOPE ALL MAINTENANCE ENTRIES AGAINST -6 WUC
ENGINE BUILD	MMICS TRE	AFM 66-378 (DSO G073)	REPLACES AFTO 781E
ENGINE STATUS	BASE COMPUTER	AFM 400-1 AFTO 1534	INPUT TO D024 AT DEPOT NOT AVAILABLE AT BASE

Table 4.7 (Continued)

DATA ITEM	SOURCE	PROCEDURE REFERENCE	COMMENT
REPAIR STATUS	MMICS/TCTO JEIM SHOP	AFM 66-278 BASE STANDARDS - DCM	REQUIRES SEVERAL MMICS TRICS PERCENT COMPLETE OR MMH BACKLOG DESIRABLE
FLYING SCHEDULE	MANUAL OR BASE COMPUTER	BASE-DEPENDENT	WILL BE AUTOMATED IN THE FUTURE

Table 4.8

Data Source Subsystems

DATA SOURCE	DATA ITEM	IMPLEMENTATION
AUTOMATED TEMS	PERFORMANCE TIME/CYCLES VIBRATION (OPTIONAL)	DPU/DDU
BASE COMPUTER	STATUS MDCS BUILD FLYING SCHEDULE ENGINE STATUS SOAP (BASE OPTION) PARTS TRACKING	MMICS
SHOP (MANUAL)	BORESCOPE REPAIR STATUS MAINTENANCE HISTORY SOAP (BASE OPTION)	ENGINE LOG/AFTO 95
CENTRAL/DEPOT	ENGINE RECORDS TCTO INFORMATION	MMICS TAPE

4.4.1 TEMS Implementation Requirements

One important source of maintenance data is the automated TEMS. The sophistication of the TEMS hardware ranges from automatic logging of usage counts to complex diagnostic/trim/troubleshooting equipment such as the F100/EDS or TF34/TEMS. Recommendations for implementation of the automated TEMS consistent with maintenance information requirements and operational procedures are summarized below.

(1) The on-board instrumentation (e.g., sensors, processor, multiplexer) and acquisition logic (e.g., sampling rate, data windows) impact the accuracy of measured data. The engine sensors are sources for performance data and for flight-line diagnostic inputs. Time and temperature are recorded to track engine life usage. The sensor complement and accuracy impact the overall capability of the performance monitoring. Table 4.5 lists important elements in the trade-offs inherent in data acquisition and instrumentation systems.

(2) On-board and off-board software must account for measurement error sources that are induced by engine disequilibrium (process noise), sensor noise, and probe dynamics. These methods improve the overall quality and accuracy of the performance estimates derived from the raw measurements.

(3) An important consideration in processing automatically acquired data is the detection and disposal of data scans that include failed or disconnected channels. In practical operation, input channels may remain failed for long periods because a maintenance opportunity has not arisen. A procedure for detection and reconstruction is clearly required. It should establish whether current values are consistent with previous measurements. Inconsistent data channels should be flagged to the user as sensor faults.

(4) On-board data storage and processor capabilities must accommodate aircraft mission and sortie rate for command-specific operating scenarios. Based on the specific engine and command implementation, trade-offs should be made between the storage and processor requirements. For example, if data compression algorithms are identified as practically viable, it might be cost effective to enhance on-board processor software to reduce on-board data storage.

Table 4.9

Sensor Requirements vs. Capability for Automated TEMS

INCREASING COMPLEXITY

MAJOR SENSOR ADDITION	ADDITIONAL CAPABILITY
TIME	MANUAL CYCLES
CORE SPEED	LCF COUNTS
TURBINE TEMPERATURE	HOT SECTION TIME
VIBRATION ACCELEROMETER	VIBRATION LEVEL/EVENTS
AMBIENT PRESSURE AMBIENT/FAN TEMPERATURE FAN SPEED	OVERALL PERFORMANCE CHECKING/TRENDING/EVENTS
BURNER PRESSURE INTERTURBINE P OR T EXHAUST PRESSURE	MODULAR PERFORMANCE TRENDING/EVENTS
GEOMETRY THROTTLE	FAULT ISOLATION LIFE CONSUMPTION
AIRFRAME ACCELEROMETER STRAIN GAGE	STRUCTURAL LIFE ASSESSMENT

INCREASING CAPABILITY

(5) The on-board processor should monitor gross engine health continuously and evaluate data consistency. Windows for automatic performance data collection should be set to ensure sufficient data to perform off-line trending and detailed engine performance analysis.

(6) Data transfer hardware must be portable and compact for operation by flight line personnel. The equipment should automatically download data from on-board storage. A limited processing capability should permit a display of data at the flight line on an exception basis. The transfer unit displays must provide the diagnostic data to support go/no-go decisions required by flight-line (AGS) maintenance operation.

(7) The off-board temporary data storage capability should accommodate aircraft sortie rates and wing requirements. The data transfer equipment must provide the capability to install, trim, and calibrate engines and support all AGS trim/troubleshooting functions without reliance on other AGE. In addition, this unit must support installation, calibration, diagnosis, and initialization of on-board TEMS hardware in a stand-alone mode.

(8) It is important that each TEMS program development includes base level (AGS) procedures for maintaining the hardware consistent with Air Force practices and within expected operating scenarios. If this is not done, acceptance of the TEMS hardware and capability by the AGS may be compromised.

(9) Deployment capability is an important aspect of Air Force operations. This scenario places special requirements on the TEMS hardware. All on-board and data transfer hardware must be deployable as required by installed aircraft mission. This requirement dictates the design of highly reliable/low maintenance equipment that is line-replaceable whenever possible. Moreover, a maintenance specialist should not be required for on-site deployment support for TEMS equipment.

(10) Given the finite storage capability of the data transfer hardware, the Air Force must evaluate alternative provisions for longer term storage of performance data at remote site for lengthy deployments.

4.4.2 Base Computer

The base computer is a repository of data files containing maintenance information. These data systems should be considered as information sources for an integrated engine monitoring capability. The functional capabilities defined by the task force require data from existing information sytems. Integration of the following base level data subsystems is recommended.

(1) MDC data should be used to reconstruct major installed maintenance actions. Coded data are used to describe the maintenance action taken, the nature of the malfunction, and the section of the engine where the work was performed (work unit code).

(2) Component replacements are recorded on a regular basis by the MMICS replacement record (TRE) and/or the manual 781E system. It is recommended that these be correlated against data entered in the maintenance data collection (MDC) system.

(3) Engine TCTO status is tracked by MMICS with a manual backup in the engine log. Both base and depot users require consistent lists of outstanding TCTOs by engine serial number. The list must be updated when new TCTOs are issued, or when outstanding TCTOs are resolved. Input should be CRT-type entry with a coordinated base level interface.

(4) The supply system is divorced from the maintenance data system (MMICS, MDCS). The task force indicated that current data on parts availability should be accessible at engine shop, but this is viewed as a significant interface effort.

4.4.3 Shop Record Information

The following data items presently located at the JEIM shop are recommended for integration into the automated data base.

(1) Major uninstalled maintenance is summarized in the significant history forms (AFTO95) filed in the engine log. A CRT entry of edited/abridged data from the log report (AFTO95) is highly recommended.

(2) Oil analysis data are currently coded, keypunched, and transferred to the San Antonio ALC via AUTODIN. The analysis of the lab data at the base

level is usually done manually. Integration of SOAP data by mass media entry with CRT edits from the SOAP lab is recommended. These data should be in a format consistent with both base and depot transfer and utilization.

(3) Borescope status reporting could be implemented in the same way as AFTO95 records. It is recommended that a borescope summary form be created and recorded at base via CRT-type entry. The precise requirement of the interface is dependent on the final definition of the base level processing system, but should be automatic after initial entry.

4.4.4 Depot/Central Data Items

Data received through the depot are directed toward engine configuration and status assessment. Base level access to the following items is recommended.

(1) Engine build documentation should be obtained from, and provided to, base MMICS. These data include the serial number, part numbers, and usage accumulation to date for each tracked component of a module or engine. Initialization of the data base requires a tape entry of the build configuration for each tracked engine. Time/cycles for each component are incremented with usage data from the TEMS.

(2) Engine/module status reporting is provided by the depot D024 system. The AF1534 forms document engine removal or changes in operational/repair status. A CRT entry should be used to update status summaries at the base level and provide the D024 record inputs to depot via AUTODIN as standard procedure.

4.4.5 Summary of Data Items and Interface Recommendations

The data items and interfaces are summarized in Table 4.10. This table forms the basis for the requirements on the hardware and software system, detailed in the following sections.

Table 4.10

Data Item and Interface For Integrated System

DATA ITEM	SOURCE	SYSTEM	AUTOMATIC INTERLINK	ALTERNATIVE INTERFACE
INSTALLED PERFORMANCE/ LIFE USAGE	ENGINE MONITORING SENSORS	TEMS	DCU/DDU	FLOPPY DISC
ENGINE BUILD DOCUMENTATION	INITIALIZATION DECK	MMICS	MMICS TELELINK	TAPE ENTRY
COMPONENT REPLACEMENT RECORD	AFTO 781E	MMICS	MMICS TELELINK	TAPE ENTRY; CRT ENTRY
MAINTENANCE DATA COLLECTION	AFTO 349	MMICS/AFLC	MMICS TELELINK	TAPE ENTRY; CRT ENTRY
SIGNIFICANT HISTORY	AFTO 95	ENGINE LOG	N/A	CRT ENTRY
TCTO ACTIONS OUTSTANDING	DD 829-1	MMICS	MMICS TELELINK	TAPE ENTRY
ENGINE STATUS	AF 1534	AF 1534	N/A	CARD ENTRY
PARTS AVAILABILITY OIL ANALYSIS PROGRAM	N/A DD 2026 DD 2027	SUPPLY SYSTEM OAP SYSTEM (SA-ALC)	N/A TBD	CRT ENTRY CRT ENTRY
BORESCOPE STATUS	INSPECTION REPORT	PROPOSED	TBD	CRT ENTRY

4.5 BASE PROCESSOR CONFIGURATION OPTIONS

Data items and interfaces have been identified to support integrated monitoring. The processing hardware at each maintenance echelon must be consistent with the resulting data availability, access, and transfer requirements. The data system to support Air Force engine management will be distributed between base and central (see Figure 4.5) facilities. The central storage facilities will be serviced by peripheral processors to support a variety of users. There are several viable options for base level implementation of the integrated engine monitoring capability.

The base central computer will be linked to the central data facility via AUTODIN II. This computer supports all engine management data systems currently in place (e.g., MMICS). Automatically acquired data and the integrated monitoring data base can be implemented in the following configurations: (1) within the base computer as a separate set of software programs and operating systems or (2) in a distributed computing environment consisting of a peripheral front-end processor (shop computers) linked to the base central facility.

The first configuration is shown in Figure 4.6. In this implementation, TEMS data are down-loaded into the data collection unit at the flight line. This AGE links with the central facility to transfer raw readings to the computer. Processing, prescreening and data management software in the central computer creates the necessary data base. The computer also must service interactive user access as in the current system. The impact of the central configuration is summarized as follows:

(1) major central computer software development must be implemented;

(2) the facility must be sized to accommodate high surge inputs from DDU dumps of data;

(3) minimum TEMS AGE is required to support the system when the unit is not deployed;

(4) there is no real-time capability beyond snapshot diagnostics during deployment; and

(5) data transfer during deployment could be a significant system design driver.

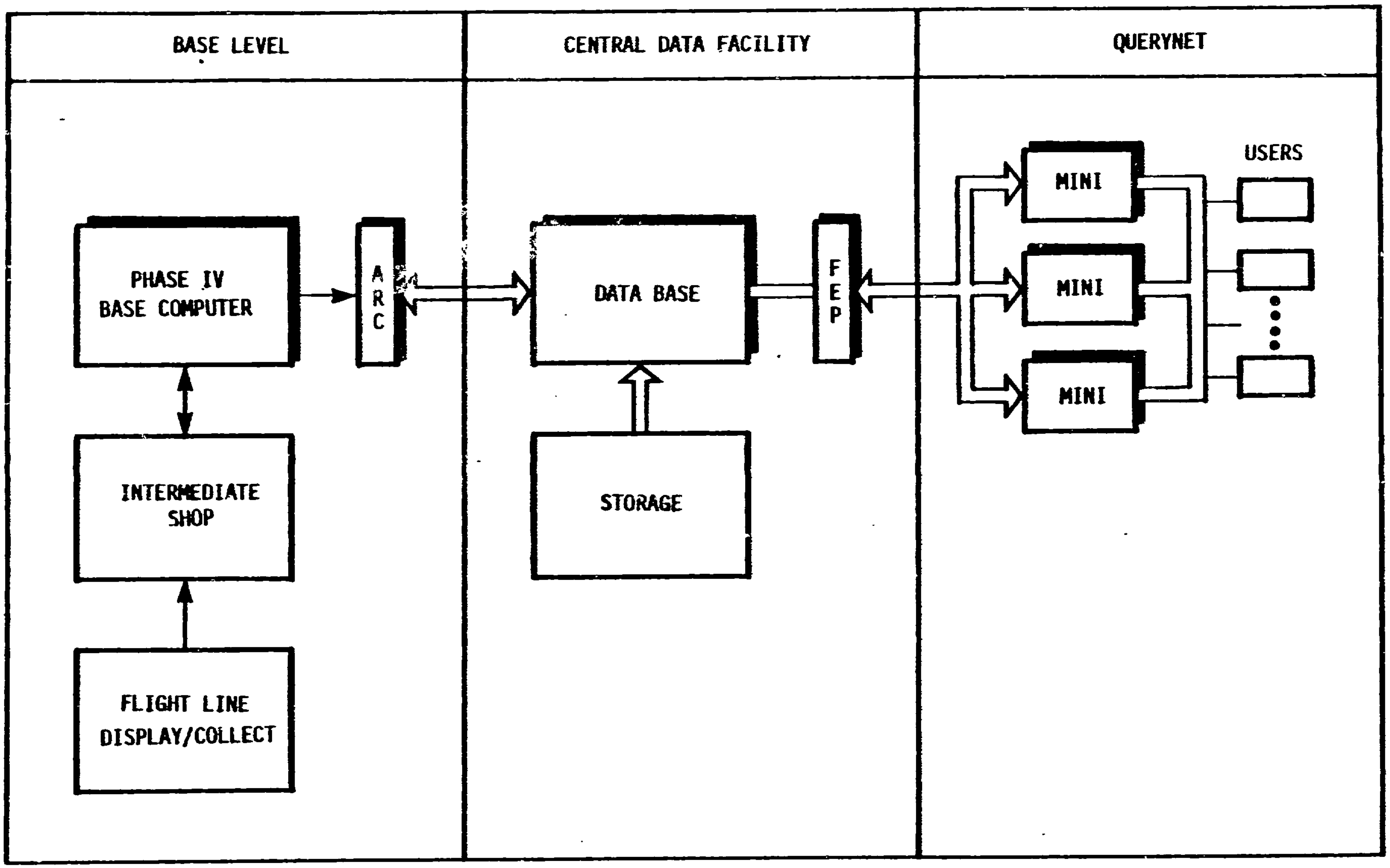


Figure 4.5 Local/Global Interface

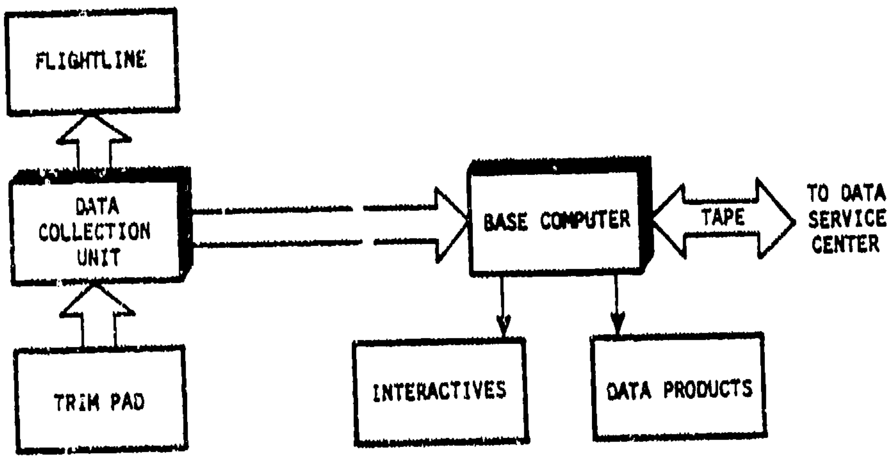


Figure 4.6 Base Central Computer Configuration To Support Automated TEMS-Acquired Data

The distributed configuration is shown in Figure 4.7. TEMS data are entered and supported by a JEIM shop data base computer. This system receives TEMS data, indexes, prescreens, and updates the local data base. User inquiry is supported in the shop area. The shop computer interfaces with the central facility during direct two-way mass transfer. The impacts on operations are summarized below.

(1) Minor base central computer software development is required since most standard data systems can be employed.

(2) Shop computer prescreens, validates, and indexes TEMS data for reduced information transfer loads to the central facility.

(3) The shop computer is dedicated to servicing user interaction to provide high response access cpability.

(4) The shop computer should be JEIM-deployable to support all intermediate functions remotely. This would provide continuous history/trending/ diagnostic capability wherever intermediate maintenance is contemplated.

The complete configuration of this base level architecture is shown in Figure 4.8 with data item sources and system interfaces identified.

4.6 SOFTWARE REQUIREMENTS

Efficient and flexible implementation of an integrated maintenance information management system should be achieved with modular and upwardly compatible software. This is crucial in light of the long life cycle typically required in Air Force management systems. Narrow assumptions of static user requirements can lead to a "fixed point" software design that is not compatible with the fact that diagnostics and maintenance information requirements evolve dynamically over the life of the engine. Wear-in deterioration of new engines exhibit different diagnostic symptoms and problems than those encountered by engines in service for several years. Specific maintenance procedures and support policies may change as a function of cost constraints.

In addition, all system software must be flexible enough to handle input from a range of monitoring systems. It is desireable that processing and data

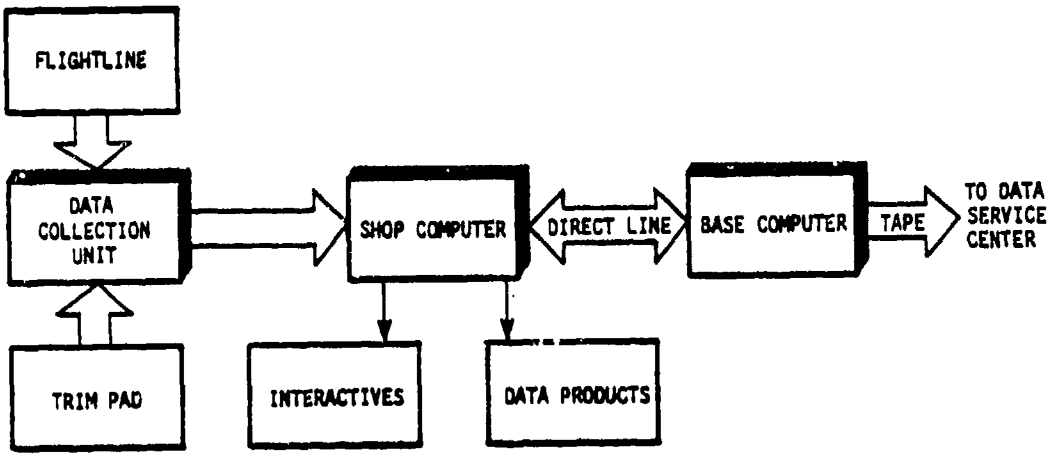


Figure 4.7 Distributed Base Architecture Supporting Automated TEMS-Acquired Data

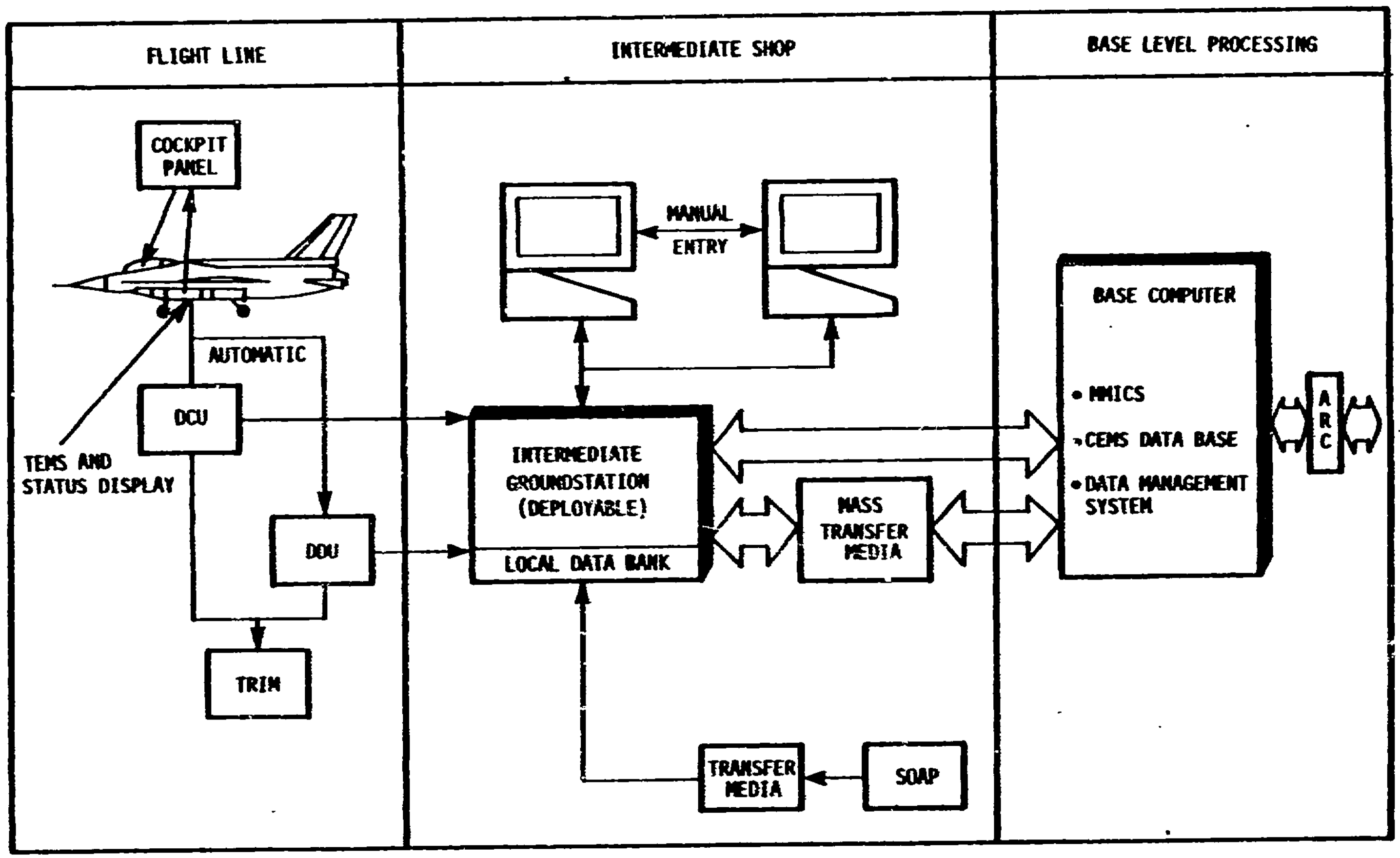


Figure 4.8 Complete Base Level Distributed Processing Scenario

management logic be generic. Acceptable software design must avoid customization to specific application equipment when possible.

The next two sections discuss an approach to software architecture and application programs recommended to implement an information management system to support performance analysis using automated TEMS inputs.

4.6.1 Architecture of the Operating System

A software design approach that facilitates efficient and flexible implementation of modular and upwardly compatible data processing is recommended. The distinctions between the operating executive and application logic are illustrated in Table 4.11.

- Processor hardware should be utilized in a most efficient manner by time-sharing limited resources such as data transfer and memory.
- Software development should use a fixed operating system established early in the development cycle.
- Applications software should be developed and implemented with minimum interaction and impact on other system functions.
- Modification, revision, transfer, and addition of software functions should be performed quickly and efficiently without impact to system operation, documentation, or performance.
- Hardware variances should be accommodated easily.

Base level storage contains filed entries for each engine. Information in the engine file should include parts configuration, aircraft identification, operating time and cycles as of the most recent recordings, and a record of data entered but as yet unprocessed.

4.6.2 Applications Software

The software architecture to support a maintenance information management system must be synthesized to support the operational scenarios envisioned for its use. This includes sequential acquisition and qualification of data,

Table 4.11

A Comparison Of Operating Executive and Application Functions

ISSUE	OPERATING EXECUTIVE	APPLICATION SOFTWARE
PURPOSE	OPERATE PROCESSOR AND ALLOCATE RESOURCES	ACHIEVE SPECIFIC FUNCTIONAL OBJECTIVES
COMMONALITY	COMMON TO SEVERAL HARDWARE ENVIRONMENTS	SPECIFIC TO LOCATION AND FUNCTION ADDRESSED
DEVELOPMENT VOLATILITY	DEVELOPED EARLY IN PROGRAM	MANY MODIFICATIONS DURING DEVELOPMENT AND TEST
RESOURCE UTILIZATION	20 %	80 %
RELIABILITY	HIGH-FIXED EARLY	CONTINUALLY IMPROVING
USER IMPACT	LITTLE	DIRECTLY IMPACTS SYSTEM OPERATION
EFFECT OF MISSION CHANGE, ENGINE MODE, MAINTENANCE PROCEDURES	NONE	LARGE

efficient user interface, multi-indexed query capability, and multi-media data transfer and output.

The operating executive coordinates access to the information during application routine execution. Two types of application software must exist. They are display functions and data processing functions (see Figure 4.9 for typical breakdown of modules).

Display functions produce data products on the CRT (interactive) or in hard copy (off-line). Using standardized program protocols, application modules should be developed easily. Data processing routines implement all automated manipulation, examination, and exception of the data. Routines in this category include engine performance analysis, trending, alarms, sensor diagnostics, etc. Development time on this software will be greatly dependent on the complexity and sophistication of the routines involved.

The software must be executable on many types of computational units, e.g., the base computer facility, central data bank computer, peripheral display processors, etc. This is a critical element in the design. The application functions necessary to perform data input, management, and output are illustrated in Table 4.12.

4.7 MAINTENANCE INFORMATION MANAGEMENT SYSTEM

Software has been developed and demonstrated to meet the requirements discussed in Sections 4.1 through 4.6. Some of the data products of the system are seen in Chapters V through VII in the discussion of the analysis of TEMS, EDS, and IECMS data. For a more comprehensive look at the system capabilities, the reader is referred to the Maintenance Information Management System user's manual.

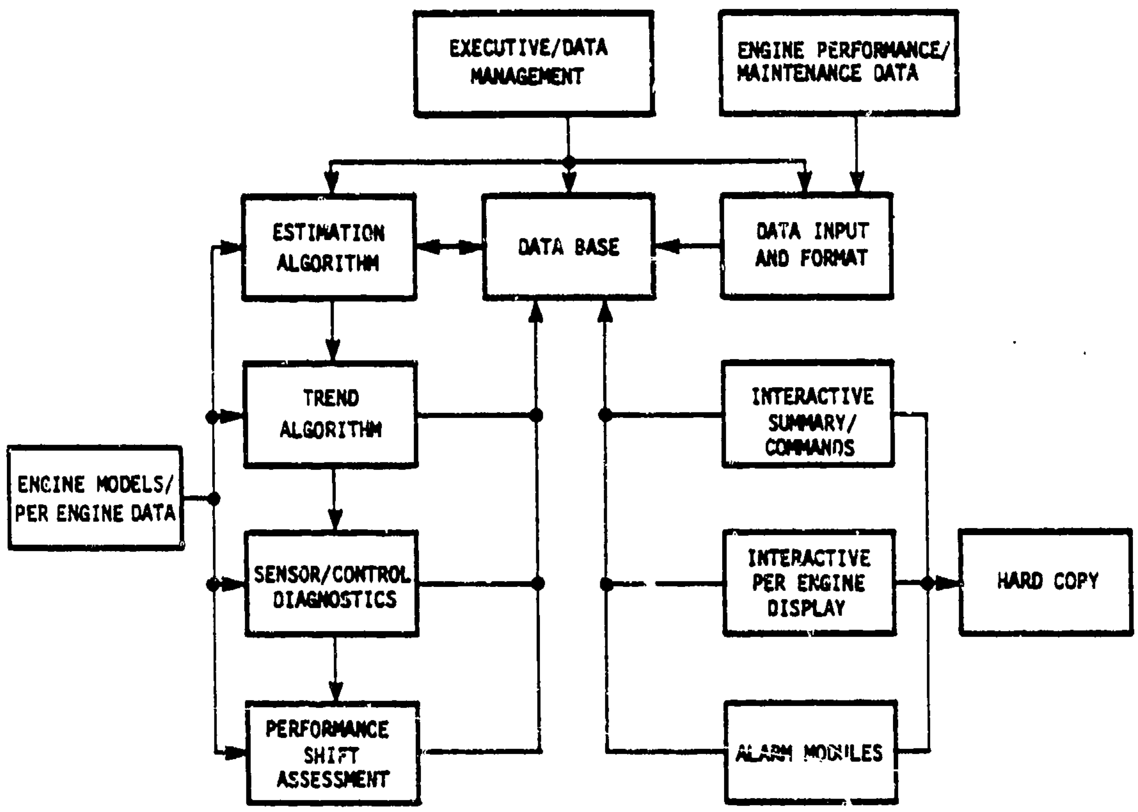


Figure 4.9 Software Modularity In Engine Monitoring and Trend System

Table 4.12

Software Functional Description Application Modules

SYSTEM FUNCTION	SOFTWARE MODULES
DATA INPUT	- PERFORMANCE DATA ENTRY - TIME/CYCLES/HOT SECTION UPDATES - MAINTENANCE/REPAIR ACTIVITY - ENGINE REMOVALS/MODULE SWAPS - INVENTORY STATUS - ENGINE FILE EDITING
DATA MANAGEMENT	- FILE MAINTENANCE - ACCESS CONTROL - ARCHIVING/BACK UP - FILE TRANSFER - INTER-PROCESSOR PROTOCOLS
ENGINE DATA ANALYSIS	- ENGINE PERFORMANCE ANALYSIS - PER-ENGINE DATE MODULE - TRENDING ALGORITHM - SENSOR DIAGNOSTICS - PERFORMANCE SHIFT CALCULATION - VIBRATION ANALYSIS - OIL ANALYSIS - MAINTENANCE HISTORY - USAGE TRACKING - EXCEPTION LOGIC
OUTPUT	- INTERACTIVE CONTROLS - SUMMARY/INDEX DISPLAY - DECISION LEVEL MODULES - HARD COPY SUMMARIES - MAGNETIC TAPE INTERFACE - TERMINAL DISPLAY DRIVERS

V. APPLICATION TO A10/TF34 TEMS FLIGHT SERVICE EVALUATION DATA

5.1 INTRODUCTION

Chapter V examines the concept of an integrated engine monitoring system within the framework of the A10/TF34 flight service evaluation. Test background is provided and highlights of the test are presented which define the diagnostic capabilities of the TEMS. Modeling activities are followed in the development of the thermodynamic cycle monitoring algorithm. Results of the algorithm development are presented Results of the analysis activities following the test helped to elucidate the feasibilities and limitations of automated turbine engine monitoring, as an independent element, and as part of an integrated set of maintenance tools. It is believed that the vehicle driving this integration is the thermodynamic cycle monitoring algorithm. With consideration given to these factors, potential impacts of the system are discussed.

5.2 TEST BACKGROUND

Before discussing the details of the test, the objectives of test data evaluation are presented as follows:

- to evaluate data accuracy, repeatability and sensor variations in TEMS data
- to develop algorithms to reduce performance data to usable parameters
- to assess applicability of test results to the engine maintenance process

The flight test was begun in November 1978 at Myrtle Beach AFBSC with five aircraft. A sixth aircraft, modified to provide structural airframe as well as engine performance data, was added in April 1979. During the formal evaluation, the TEMS-equipped aircraft had acquired 1385 flights and 2233 flight hours. A flight service evaluation summary is presented in Table 5.1, which compares the test aircraft to a control group [43].

With the A10/TF34 TEMS flight test, an abundant amount of diagnostic and trending data became available. Data included in-flight engine data, oil analysis results from the SOAP system, maintenance history records from the maintenance data collection system (MDCS), and engine configuration data from the parts-tracking element of the maintenance management information control system (MMICS) [44]. The data covered a 12-month period of test performance (January to December 1979) for 12 TEMS engines. The data provide the tool with which to evaluate an automated TEMS and its integration with other maintenance management tools employed by the Air Force. A description and historical background of the TEMS is now presented.

The A10 TEMS is designed to enhance flight line diagnostics, engine troubleshooting, and trim procedures. The system is a snapshot recorder which records all measured signals when

- an engine parameter exceeds a threshold value
- the pilot triggers a record option
- certain preprogrammed flight conditions (e.g. take-off, cruise) are met

The data frames consist of several engine variables, engine and airframe serial number identification, vibration levels, and time/cycle information.

The occurrence of an event is indicated on an engine status panel. Exceedance limits are related to a malfunction code that can be examined on a flight line display unit with all the measurements taken in conjunction with the event. Normal operating data are collected without display and transferred to a ground station for storage on a floppy disc and later examination. Figure 5.1 is a block diagram of the TEMS configuration.

The TEMS was initially flight-tested by the Air Training Command (ATC) on the J-85 engine of the T-38 aircraft at Randolph Air Force Base. The results of this test were somewhat disappointing. The system flagged slightly less than 5 percent of the engine malfunctions <u>independent</u> of a pilot squawk or ground crew observation. The J-85 is a relatively mature engine normally operated in a benign training environment and maintained by experienced

Table 5.1

Summary of A10/TF34 Test Flight Evaluation

	TEMS AIRCRAFT	CONTROL AIRCRAFT
FLIGHTS	1,385	1,127
FLIGHT HOURS	2,233	1,856
ENGINE REMOVALS	4	0
GROUND ABORTS	13	7
AIR ABORTS	3	0
MMH/FH	0.82	0.35
DOWN TIME/FH	0.33	0.71
NMCM (HOURS)	958	1,247
SUPPLY DEMANDS	160	117
TEMS MHH/FH	0.021	

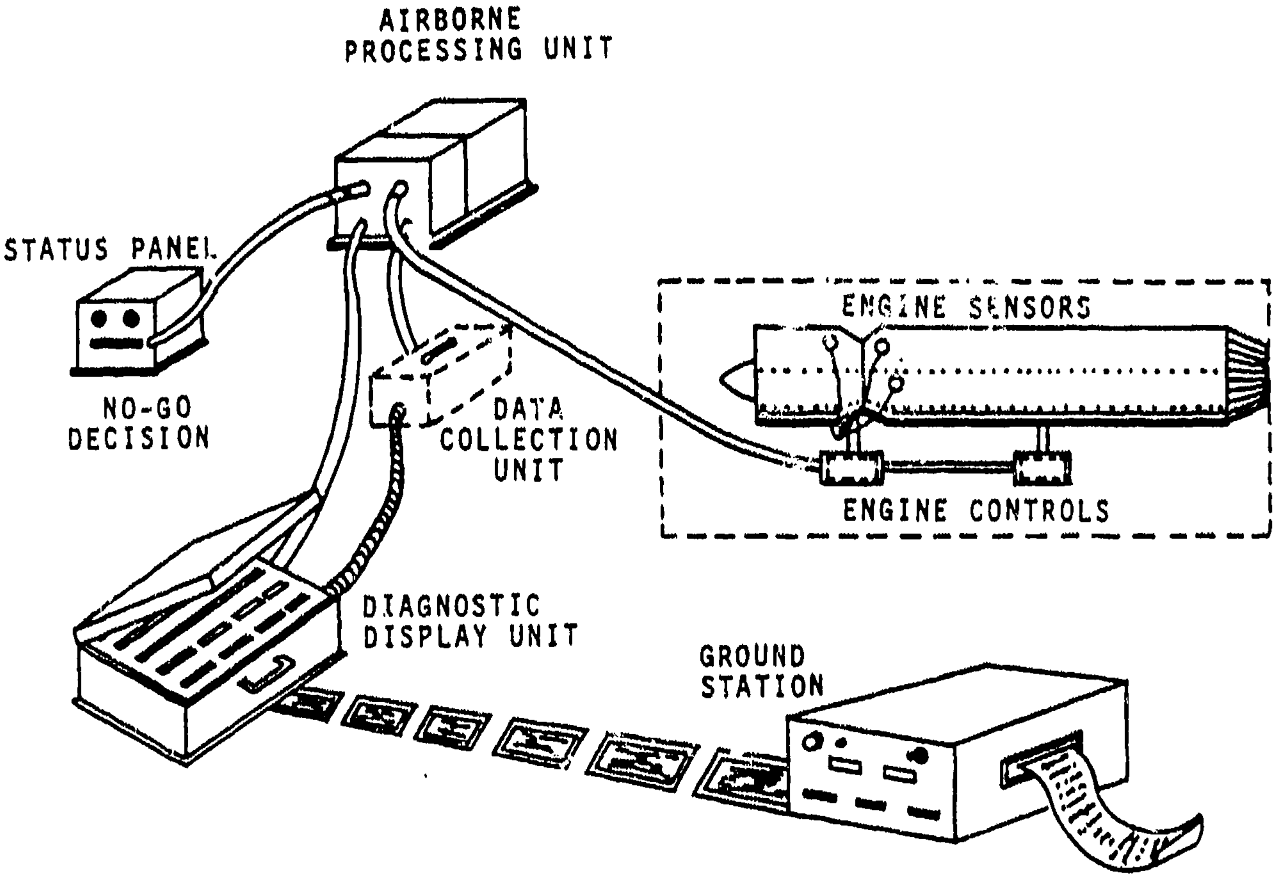


Figure 5.1 TEMS Hardware Configuration

personnel. The number of problems typically experienced by the engine is not high. It was reported, however, that the monitoring system did provide valuable information that reinforced a cause-and-effect interpretation of certain engine problems [44].

After the ATC evaluation, the TEMS aircraft were transitioned to the Tactical Air Command (TAC) for flight evaluation in a more severe operating environment with a demanding mission profile. Encouraging results in this experiment motivated TAC and AFLC to transfer hardware for further systems evaluation on six A10 aircraft.

The distribution of TEMS-detected events during the 12-month A10 flight service evaluation is presented in Figure 5.2. The large number of oil pressure fluxes was the result of software problems. Problems with wiring installation and loose vibration sensors affected the incidence of vibration events. The high level of VG events was attributed to a discontinuity in the schedule curve that was progammed into the TEMS. These system problems resulted in a high false alarm rate during the early portion of the evaluation. After the appropriate fixes were implemented, the TEMS stabilized to a much lower alarm rate and the quality of the data improved dramatically.

Table 5.2 summarizes the effectiveness of the TEMS using the categorical criteria of the test plan. The criteria are as follows:

Good: TEMS indicates no discrepancy has occurred.

Type 1: Pilot and support personnel report discrepancy along with TEMS.

Type 2: Pilot and support personnel report discrepancy for which the TEMS is programmed to detect; however, the TEMS indicates no problem.

Hit: An engine discrepancy occurs and is correctly identified by the TEMS.

Type 1: TEMS alone identifies fault which requires a maintenance action.

Type 2: Both TEMS and support personnel or pilot detect discrepancy which requires a maintenance action.

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SOURCE: ASD MALTRAN PROGRAM

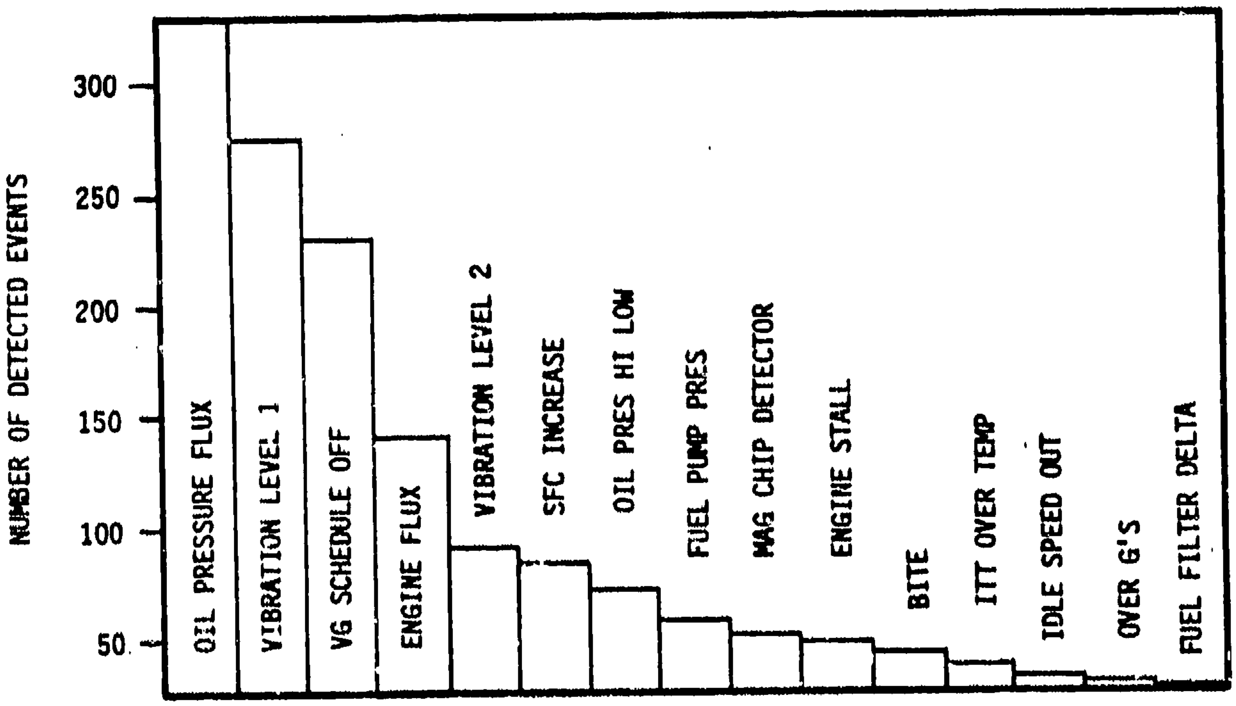

Figure 5.2 TEMS Detected Event Summary [44]

Table 5.2

Categorical Analysis Per Test Plan 1 November Through 31 October 1979 [44]

NUMBER OF FLIGHTS	TEMS FLIGHT HOURS	PILOT FLIGHT HOURS	GOOD		HITS				OUT OF SCOPE	FALSE ALARMS
			1	2	1	2	3	4		
1,289	2,014	2,233	597	3	5	10	249	2	6	65

	ACCURACY TOTAL	ACCURACY PERCENTAGES
GOOD	1,208	93.716
HIT	15	1.241
FALSE ALARM	65	5.042

Type 3: TEMS alone identifies a discrepancy (usually a limit exceedance), but the severity and duration of the problem does not require immediate maintenance.

Type 4: Engine problem identified by analysis of TEMS data (a malfunction record, or pilot report does not indicate a problem).

Miss: A discrepancy occurs which the TEMS is programmed to detect; however, no discrepancy is recorded.

False Alarm: TEMS indicates an engine malfunction when none has actually occurred.

Out of Scope: An engine discrepancy occurs, but is not programmed in the TEMS for detection.

Results indicate that this version of the TEMS had matured over its predecessor on the J-85 engine. The test was conducted on a non-interference basis. Consequently, emphasis was placed on diagnostics, and full TEMS utilization for directing maintenance was compromised.

5.3 THERMODYNAMIC CYCLE MONITORING ALGORITHM DEVELOPMENT

The following section of Chapter V discusses the way in which the theory presented in Chapters II and III has been applied to the A10/TF34 TEMS flight service evaluation data. The objective of this effort is to develop algorithms which reduce TEMS data to usable performance parameters. Ultimately, the goal is the prediction of engine failure by means of a fault estimation algorithm. To simplify the discussion of results obtained during algorithm development, it will be treated as a three-step process:

(1) Data screening, including windowing and sensor fault detection, isolation, and accommodation.

(2) Development of models for use in estimating engine performance parameters.

(3) Reduction of performance parameters to module- directed health ratings.

Each step of the development will be followed, observations will be illustrated, and results will be presented.

5.3.1 Data Screening

Production of accurate performance monitoring results depends on the quality of data used in the algorithmic models. Prior to developing a QLR model for the TF34/A10 TEMS data, the data were analyzed to determine appropriate usage profiles and levels of sensor noise. Downstream in the algorithm development process, appropriate fault parameters were chosen.

The first stage of the screening process occurs on-board the A10 with the TEMS recording logic. Data are recorded when one of six window conditions is satisfied by the aircraft and engine. These window conditions are shown in Table 5.3. For the performance analysis, data were chosen from the trim, cruise performance, and take-off windows. For 12 installed engines over the 12-month period (for which data were available), over 7000 data scans were produced.

Not all of these data represent the normal operating conditions because of sensor failures, sample outliers, equipment malfunction, and off-nominal window conditions. The data were screened to eliminate all scans with hard sensor failures. Nonrepresentative points were also screened to obtain a more uniform data sample. Little information is lost in this process when a large population is used. There were 6100 valid points after this screening process. Figure 5.3 shows a sample scatter plot of stabilized TEMS data before screening. The screened data are shown in Figure 5.4. Table 5.4 shows the final screening criteria used in the data selection process. Sample data scatter plots are shown in Figure 5.4. The data uniformity is significantly enhanced in all channels except VG. The VG data contain significant outliers. Since this variable is not used in the model development, no attempt was made to screen this channel.

5.3.2 Model Development

As explained in Chapters II and III, the procedure for estimating engine fault parameters requires a baseline model and a fault parameter (or performance) model. The engine baseline model was generated using processed

Table 5.3

A10 TEMS Data Acquisition Windows

TYPE	DESCRIPTION	CONDITIONS
1	TAKE-OFF	- ENGINE ON - NG > 56% - IN-AIR SIGNAL TRANSITION - KCAS > 100 KNOTS
2	CRUISE	- NG COR > 85.4% - |PLA RATE| < 1^{o}/2 SEC FOR > 16 SEC - |T2C RATE| < 1^{o}/2 SEC FOR > 16 SEC - NO GUN FIRE - 200 < KCAS < 300 KNOTS - 2500 < ALT < 20,000 FT - $\alpha < 15^{o}$
3	TRIM	- NG COR > 85.4% - |PLA RATE| < 1^{o}/2 SEC FOR > 60 SEC - |T2C RATE| < 1^{o}/2 SEC FOR > 60 SEC - NO GUN FOR > 60 SEC - |KCAS RATE| < 30 KN/MIN FOR > 60 SEC - ALT < 10,000 FT - $\alpha < 15^{o}$ - PLA > 50^{o}

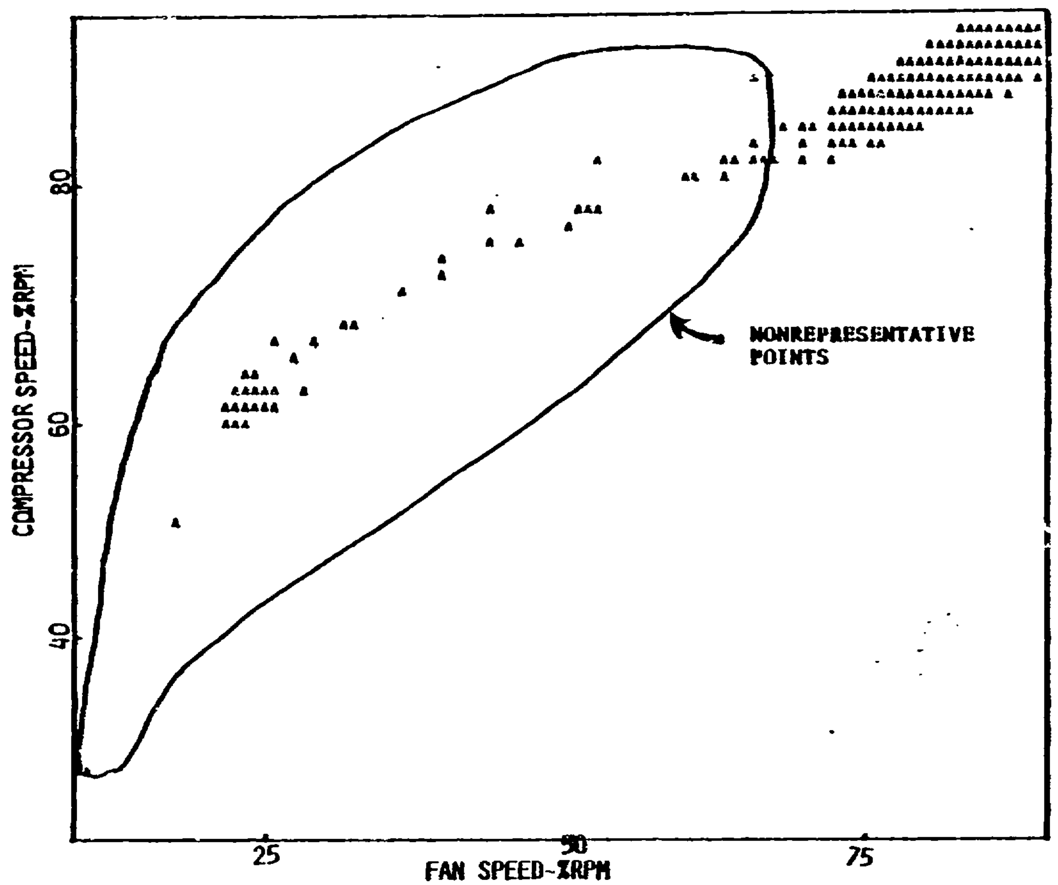

Figure 5.3 Raw TEMS Stabilized Scans

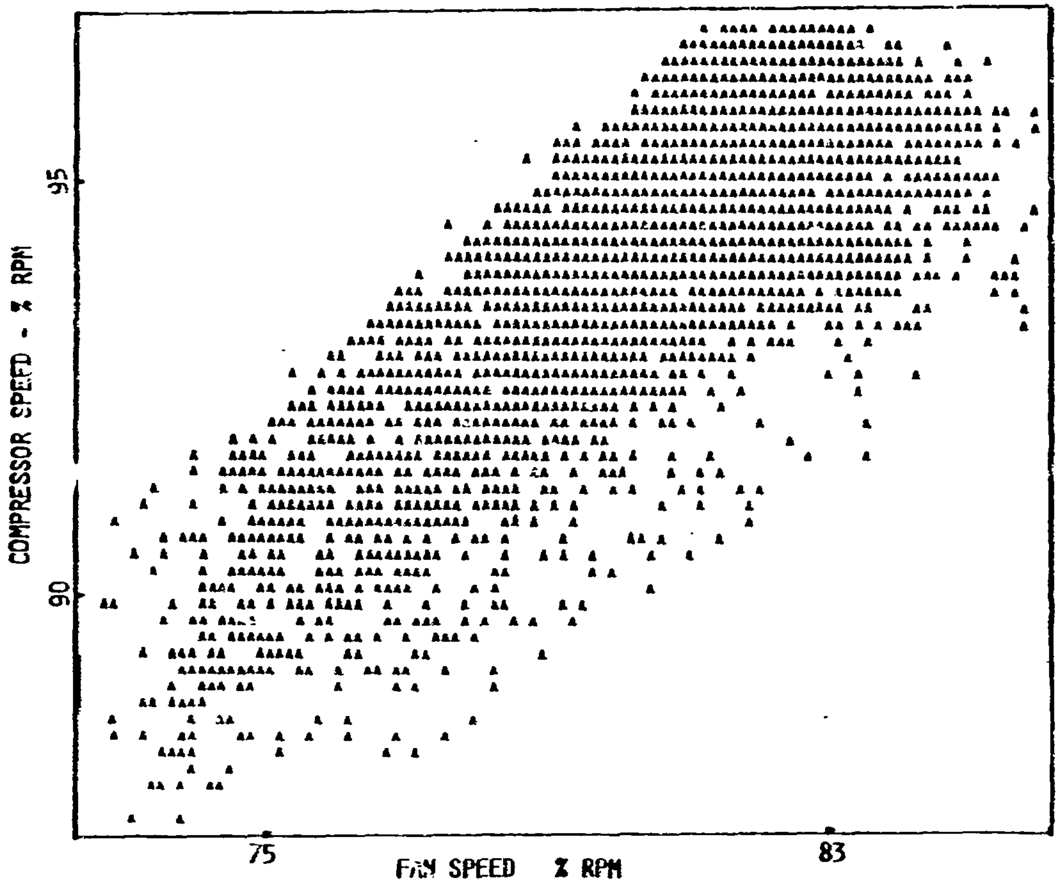

Figure 5.4 TF34/TEMS Screened Data Scans

Table 5.4

Final Data Selection Criteria

CRITERIA
WINDOW = 1, 2, OR 3
90% > NF > 71.5%
97.1% > NG > 86.6%
100^{o} > T2C > 0^{o}
3800 PPH > WF > 1237 PPH
70.6 PSIA > PT5 > 0 PSIA
342 PSIA > PS3 > 116 PSIA
831°C > ITT > 610°C
40°C > OAT > -34.2°C
PS3 < 4.86 PT5 - 72.6 PSIA
PS3 > 4.53 PT5 + 29.6 PSIA
PS3 > 0.0777 WF + 61.5
PS3 < 0.0777 WF - 0.5

TEMS data, while the fault parameter model was extracted from engine status deck data.

Baseline models were derived from the filtered TEMS data base for 11 variables. Residual analyses were performed on each of the models. Results of the analyses are listed in Table 5.5. Standard deviations for the models are shown in comparison with the accuracy specified for the sensor hardware. It can be seen that the channel fit error is significantly greater than the error which is latent in the sensor hardware design. The differences are explained by uncorrelated residuals which can be attributed to:

- engine-to-engine variations
- window effects
- stabilization
- sensor errors
- deterioration
- nonstationary processes
- other non-observable phenomena

An illustration of the residual analysis results is shown in Figure 5.5. The random distribution of the residuals about zero is an indication of the correctness of the model. Figure 5.5 shows a sample plot of PS3 residual versus total engine operating time for one engine. A dashed line on the plot indicates a gradual decline in the PS3 residual with time. This trend may reflect a long-term engine degradation.

In addition to providing a visual tool for the evaluation of regression models, residual plots depict outliers. Figure 5.6 shows the effects of soft PS3 and PT5 sensor failures. The NF vs. PLA plot in Figure 5.7 shows three PLA failures. From this plot it is not clear whether the PLA or NF sensor has failed. The sensor algorithm described in Chapter III not only detects failures but <u>isolates</u> them; in this example, the PLA failure was isolated. Soft ITT sensor failures are seen in Figure 5.8. The ITT sensor failure has been confirmed by MDC data. The failed channels are reconstructed before the data are passed to the estimation algorithm. This prevents the effects of <u>sensor</u> failures being interpreted as <u>engine</u> or module failures. These very promising results indicate the power of the sensor diagnostic algorithm and its usefulness in the processing of engine data.

Table 5.5

Baseline Model Accuracy

SENSOR	CHANNEL FIT ERROR 1	HARDWARE SPECIFICATION
PS3 (PSIA)	2.8	1.8
PT5 (PSIA)	1.3	0.4
ITT (^{o}C)	10.6	3.0
NG (% RPM)	.41	0.1
WF (PPH)	76.	50.
NF (% RPM)	.42	0.1
T2C (^{o}C)	2.6	1.0
PTO (PSIA)	.29	.12
DPAMB (PSIA)	.34	0.6

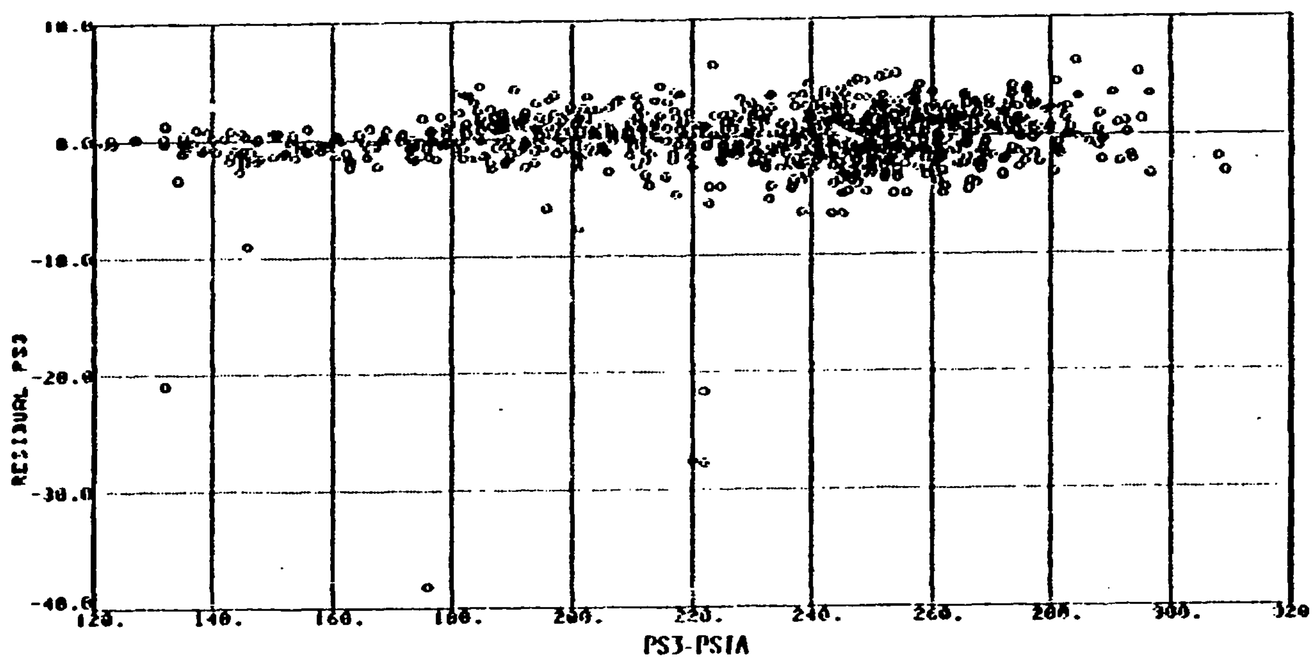

Figure 5.5 Residual Plot For PS3 Model-All Engines

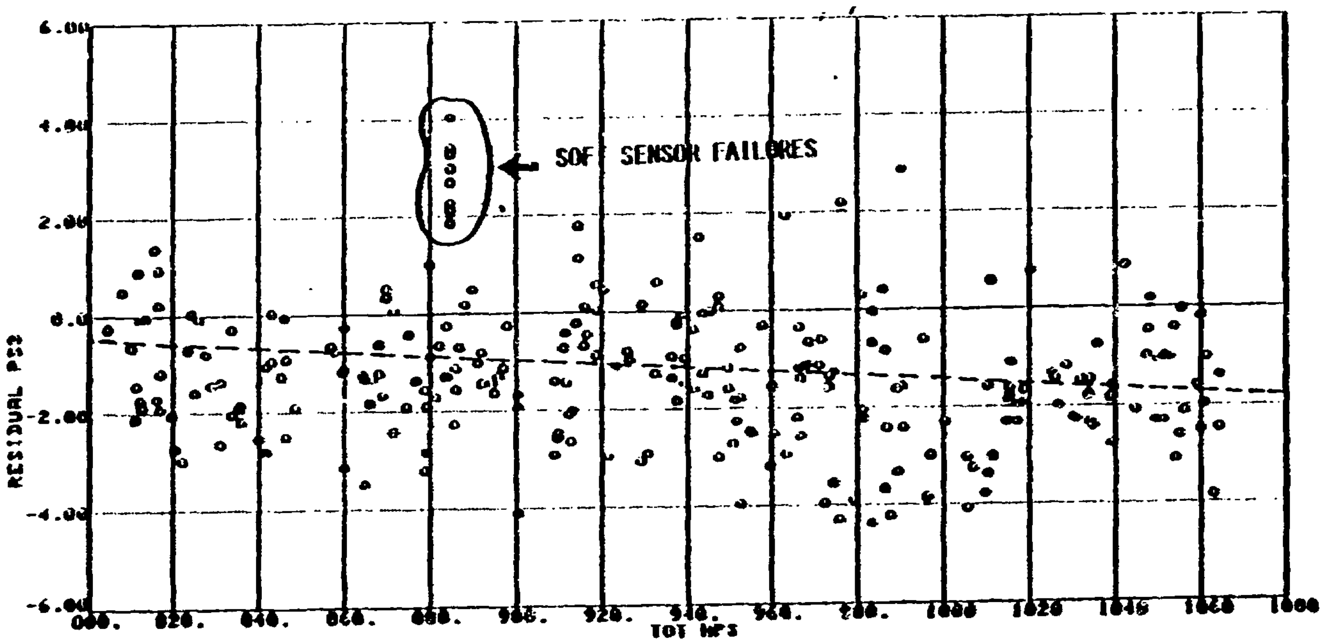

Figure 5.5 (Con't.) PS3 Model Residual Showing Long Term Trend

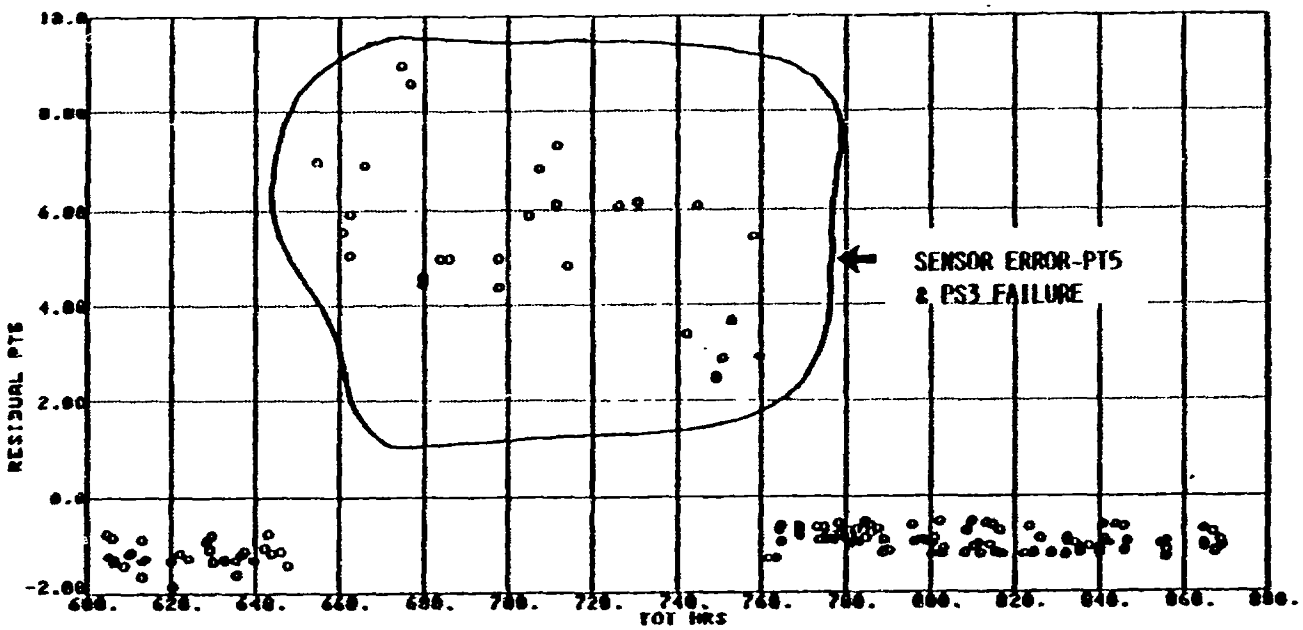

Figure 5.6 PT5 Model Residual Showing Effect of Failed Sensors

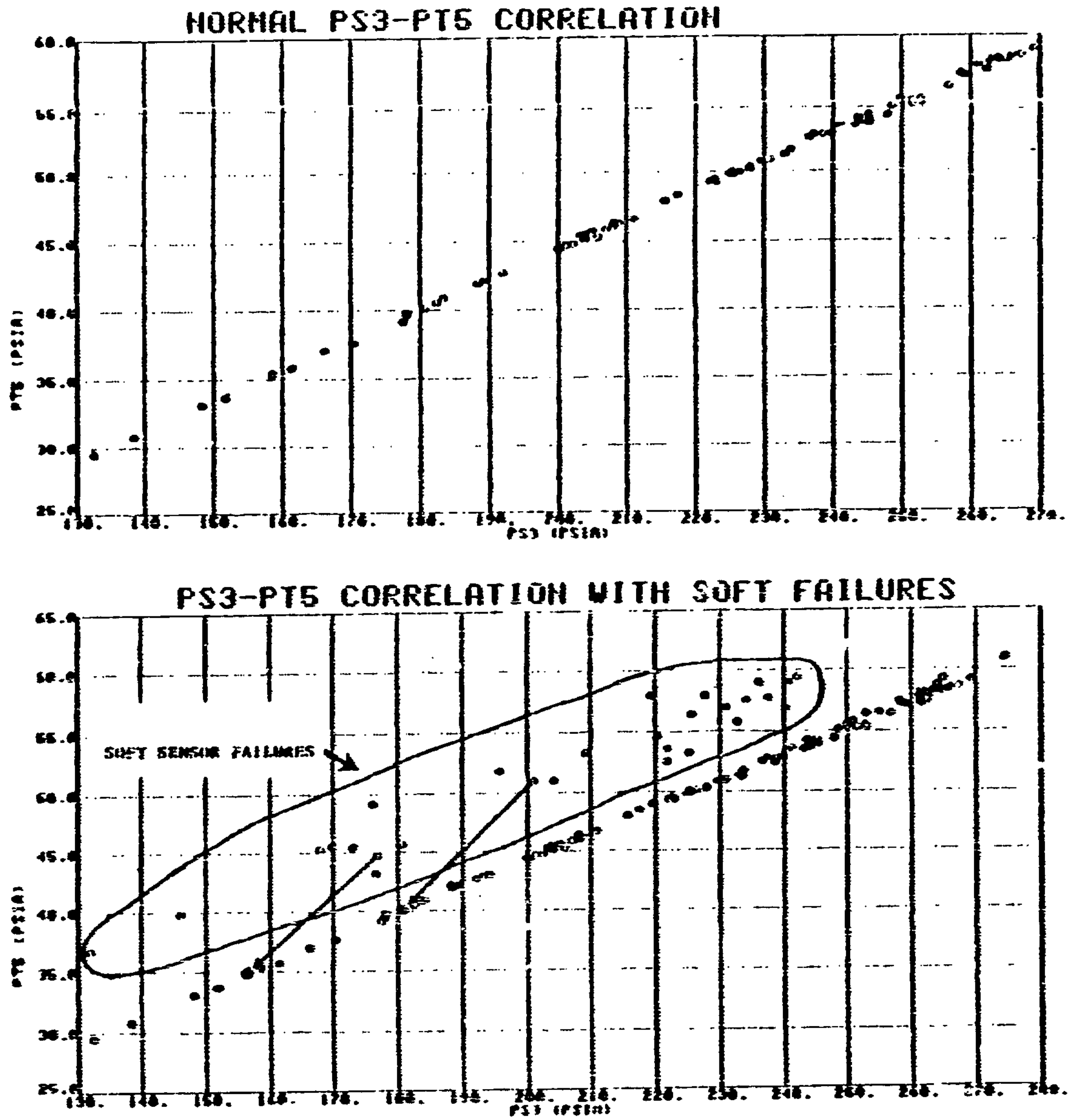

Figure 5.6 (Con't.)

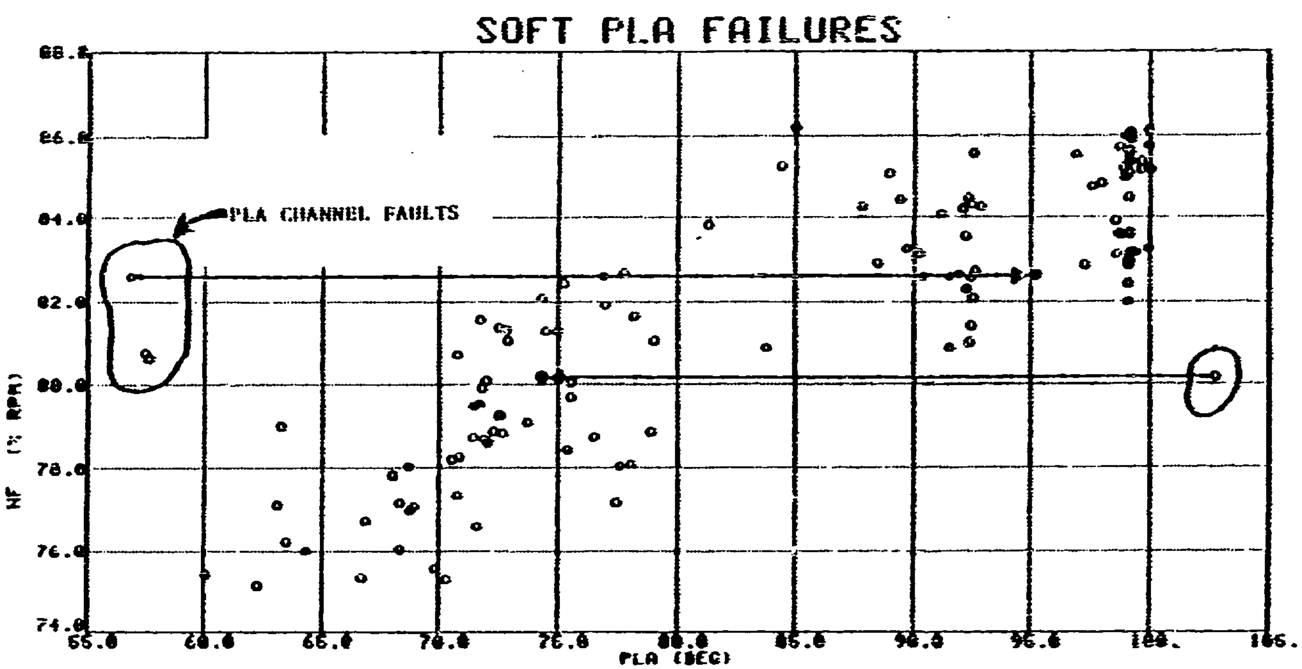

Figure 5.7 Soft PLA Failures

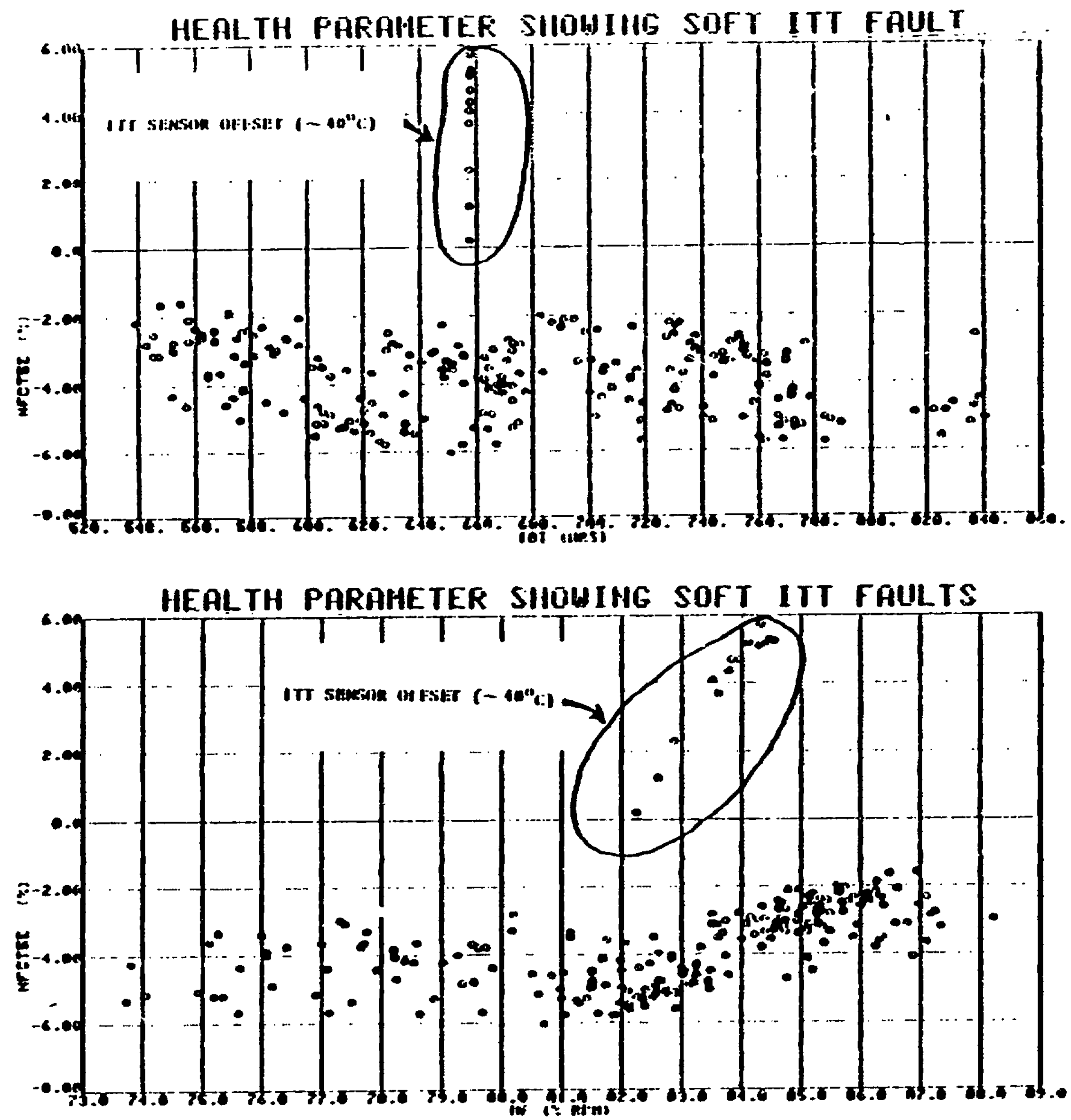

Figure 5.8 Plots Showing ITT Sensor Faults

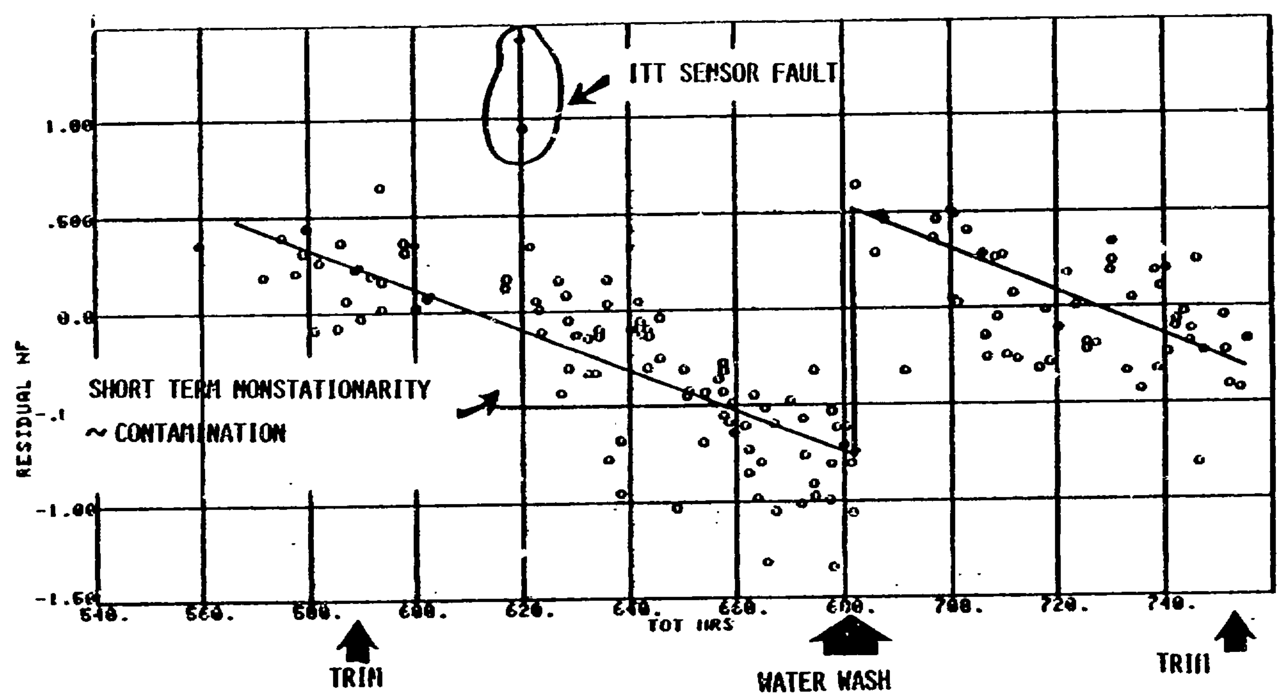

Figure 5.8 (Continued)

The fan speed residual for a single engine is shown in Figure 5.8. The residual plot shows short-term engine deterioration and a residual NF jump which is correlated with a maintenance action. The residual levels are used by the estimation/filtering algorithm to produce module health indices. The health indices are quantitatively significant, include uncertainty levels in the estimates, and are directed to an engine component or module. While the residual levels are related to the module health indices, the latter are operationally significant quantities.

Using a procedure similar to that used in developing baseline models, fault models were also generated. These models, however, were extracted from TF34 status deck data. The data base used for this program was created by executing the status deck over a range of flight conditions. For each set of flight conditions, the program was executed while varying engine component efficiencies and flow areas (i.e., fault parameters).

Five variables (PS3, PT5, ITT, NG, and WF) describing engine operation were modeled in terms of 11 fault parameters. Definitions of these fault parameters are given in Table 5.6. By analyzing the residuals of these models, strong correlations between dependent and independent variables were identified. Results of the analyses are shown in Table 5.7. For example, PT5 is strongly correlated with $\Delta\eta_{FAN}$, ΔA_{FAN}, $\Delta\eta_{HC}$, ΔA_{HC}, $\Delta\eta_{LT}$, ΔA_{LT}, and ΔA_8.

5.3.3 Lumped Parameters - Module Indices

As explained in Chapter III, to establish reasonable error levels, a limited set of fault parameters should be estimated. By examining the dispersion matrices for cases when from one to six parameters are estimated, it was decided to lump the fault parameters into three parameters (see Table 5.8). Three module-directed rating parameters result, which are linear combinations of the original 11 fault parameters. These ratings are then averaged to obtain the net rating for the overall engine.

Table 5.6

Fault Parameter Definitions

$\Delta\eta_{FAN}$	FAN EFFICIENCY DELTA
ΔA_{FAN}	FAN AREA DELTA
$\Delta\eta_{HC}$	CORE EFFICIENCY DELTA
ΔA_{HC}	CORE AREA DELTA
ΔW_{BLD}	BLEED FLOW DELTA
$\Delta\eta_{BURN}$	BURNER EFFICIENCY DELTA
$(\Delta Pr)_{BURN}$	BURNER PRESSURE RATIO DELTA
$\Delta\eta_{HT}$	HIGH-PASS TURBINE EFFICIENCY DELTA
ΔA_{HT}	HIGH-PASS TURBINE AREA DELTA
$\Delta\eta_{LT}$	LOW-PASS TURBINE EFFICIENCY DELTA
ΔA_{LT}	LOW-PASS TURBINE AREA DELTA
ΔA_8	AUGMENTOR AREA DELTA

Table 5.7

Performance Model

EQUATION	$\Delta\eta_{FAN}$	ΔA_{FAN}	$\Delta\eta_{HC}$	ΔA_{HC}	ΔW_{BLD}	$\Delta\eta_{BURN}$	$(\Delta Pr)_{BURN}$	$\Delta\eta_{HT}$	ΔA_{HT}	$\Delta\eta_{LT}$	ΔA_{LT}	ΔA_{8}
PS3	X	X	X	X	X		X	X	X	X	X	X
PT5	X	X	X	X						X	X	X
ITT	X	X	X	X	X	X	X	X	X	X	X	X
NG	X	X	X	X			X	X	X	X	X	
WF	X	X	X	X	X	X		X		X		

Table 5.8

TF34/TEMS Identifiability

ASSUMPTION:

- NOISE LEVELS FROM DATA ANALYSIS
- FIVE PERFORMANCE EQUATIONS
- DISTRIBUTION OF FLIGHT POINTS
- SINGLE-POINT ESTIMATOR

DISPERSION	
NUMBER OF PARAMETERS	MINIMUM ERROR
1	0.2%
2	0.4%
3	1.6%
4	2.2%
5	4.5%
6	LARGE

THREE-PARAMETER SET SELECTED

5.4 HIGHLIGHTS OF RESULTS

The processing of TEMS data by the TCM algorithm culminates with estimates of three module-directed rating parameters; a low spool rating parameter (LOSR), a high pressure turbine parameter (HPTR), and a core parameter (CORR). Also computed is a net engine rating (NETR) which is the numerical average of the three module parameters. Illustrations of the results of the TCM algorithm are now presented.

Figure 5.9 shows examples of the NETR, CORR, HPTR and LOSR rating parameters as a function of total engine operating time (TOT) for engine 5226. Steady engine deterioration between 600 and 760 operating hours is reflected by a decreasing net engine rating. A water wash of engine 5226 at TOT = 760 hours results in an improvement in the net engine rating. A period of slow engine degradation then follows.

Closer examination of the module parameters in Figure 5.9 shows that the maintenance action at 760 hours results primarily in an improved core rating. Apparently, heavy gun gas ingestion has a significantly greater effect on the low-spool module. Similar results occur for the 5237 engine as shown in Figure 5.10.

These plots confirm that the TCM algorithm can reduce engine monitoring data to operationally significant module health indices. They also provide graphic evidence of the trending capabilities of this analysis tool, and suggest its application for the purpose of predicting or scheduling maintenance actions. Conceivably, the lines drawn to fit trend plots could be extrapolated to predetermined rating levels, at which time a maintenance action should be scheduled.

Figure 5.11 provides an examination of short-term versus long-term trends. For example, the short-term improvement in the net rating of engine 5237 at 400 operting hours corresponds to an engine water wash. However, the single trend line (which suppresses short-term improvements) shows the long run effects of gradual engine wear. Additional plots indicate that this short- and long-term trend phenomena is observable in many engines

ENGINE PROFILE
MYRTLE BEACH AFB

E5226
0552R

STATUS	FMC
PACER ITEM	693/6800 L (HPT BLD)
NET GPA	100.0 %
TAT I	131
TAT II	603
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.6/ 6.0EFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	866.8 HRS
CYCLES	693 C (810L)

DIAGNOSTICS

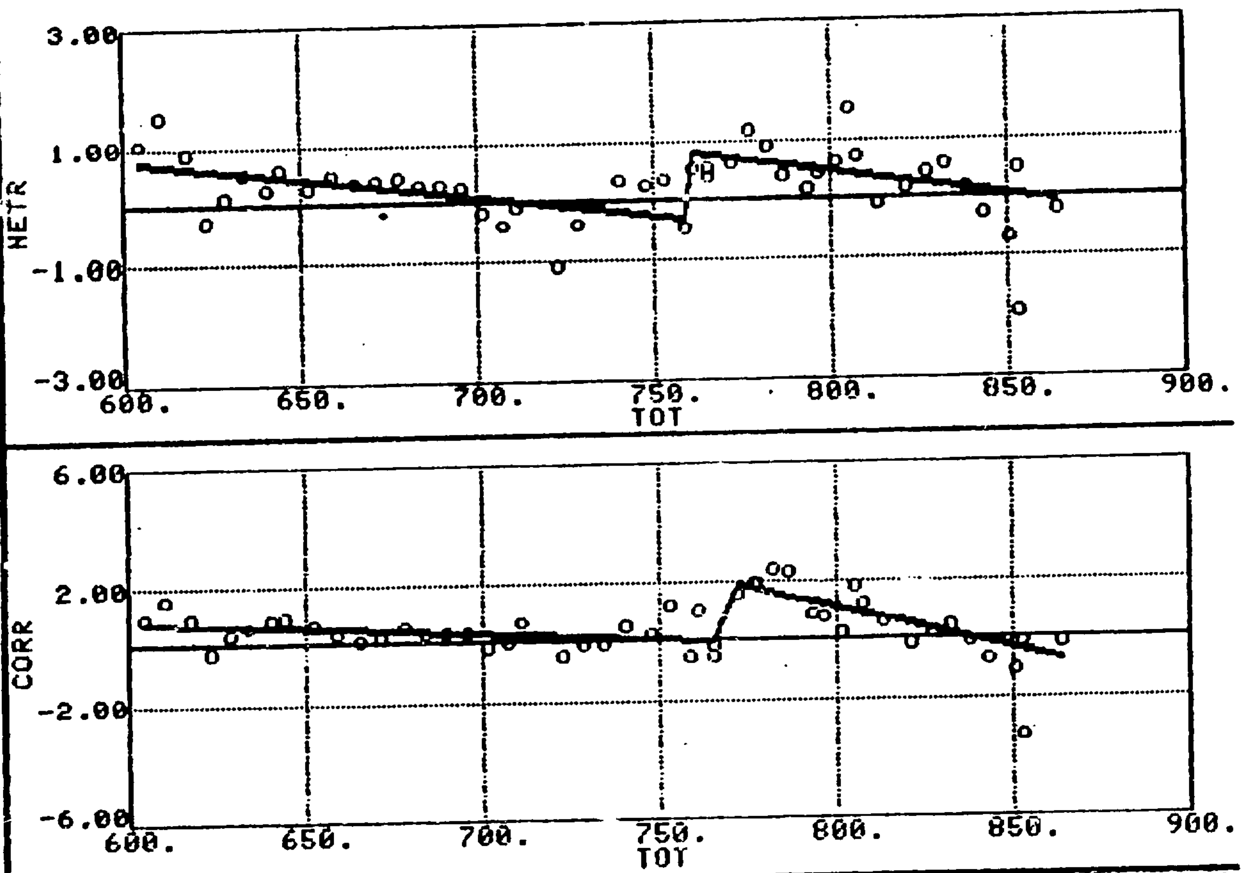

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Figure 5.9 Health Indices for E5226

ENGINE PROFILE
MYRTLE BEACH AFB

E5226
0552R

STATUS	FMC
PACER ITEM	693/6800 C (HPT BLD)
NET CPA	100.0 %
TAT I	131
TAT II	603
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.6/ 5.0EFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	866.0 HRS
CYCLES	693 C (010L)

DIAGNOSTICS

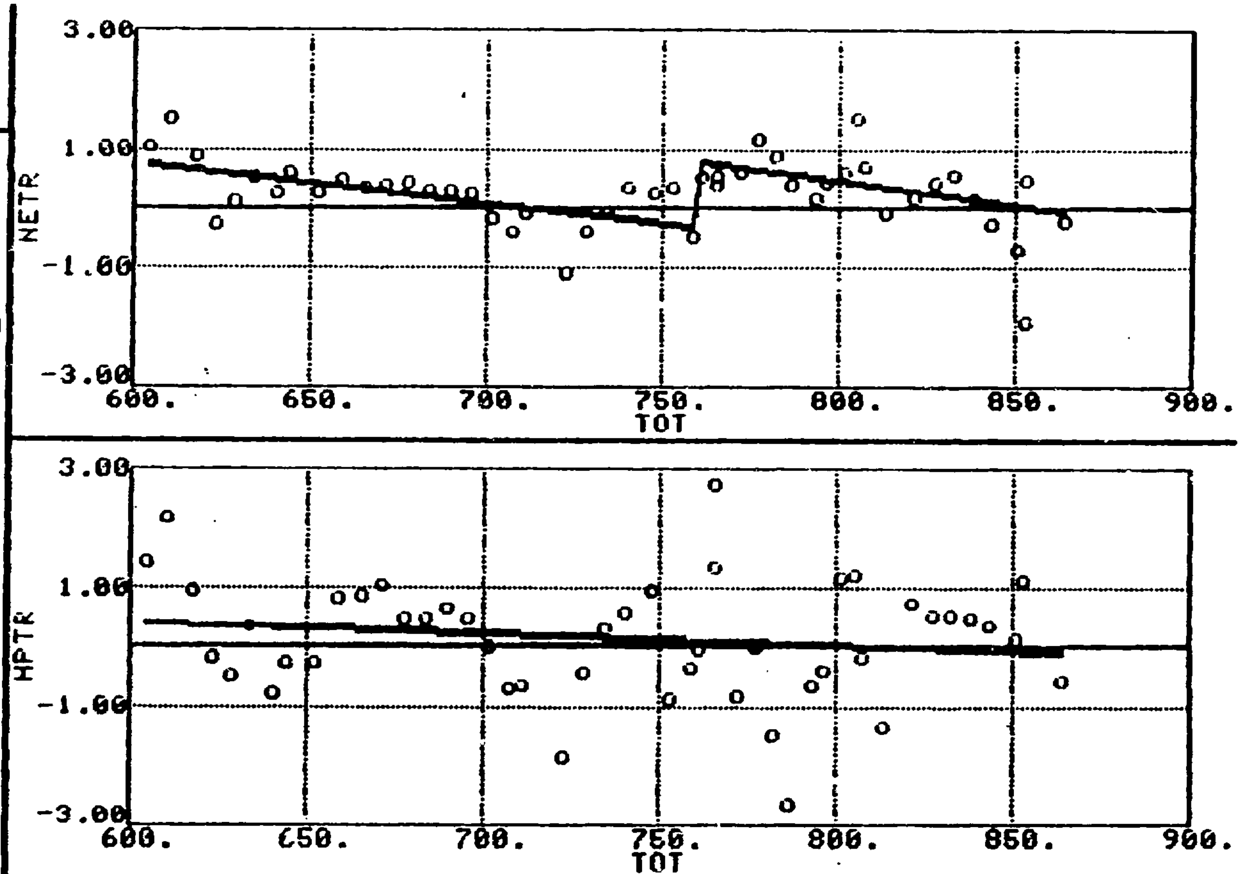

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Figure 5.9 (Continued)

ENGINE PROFILE
MYRTLE BEACH AFB

E5226
0552R

STATUS	FMC
PACER ITEM	693/6800 C (HPT BLD)
NET CPA	100.0 %
TAT I	131
TAT II	603
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.6/ . 5.0EFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	865.8 HRS
CYCLES	693 C (810L)

DIAGNOSTICS

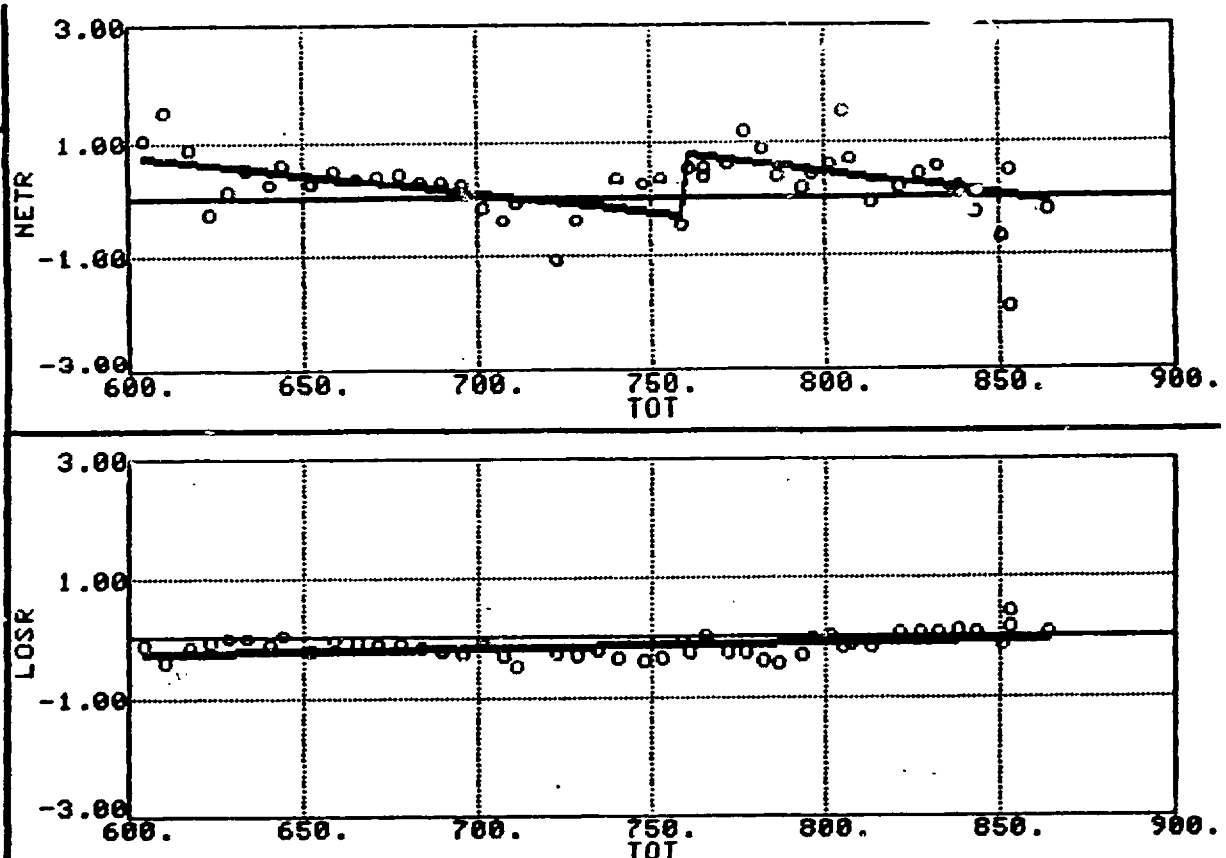

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Figure 5.9 (Continued)

ENGINE PROFILE
MYRTLE BEACH AFB

E5237
0554L

STATUS	FMC
PACER ITEM	452/6800 C (HPT BLD)
NET CPA	100.0 %
TAT I	56
TAT II	636
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	1.8/ 5.0EFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	691.9 HRS
CYCLES	452 C (810L)

DIAGNOSTICS

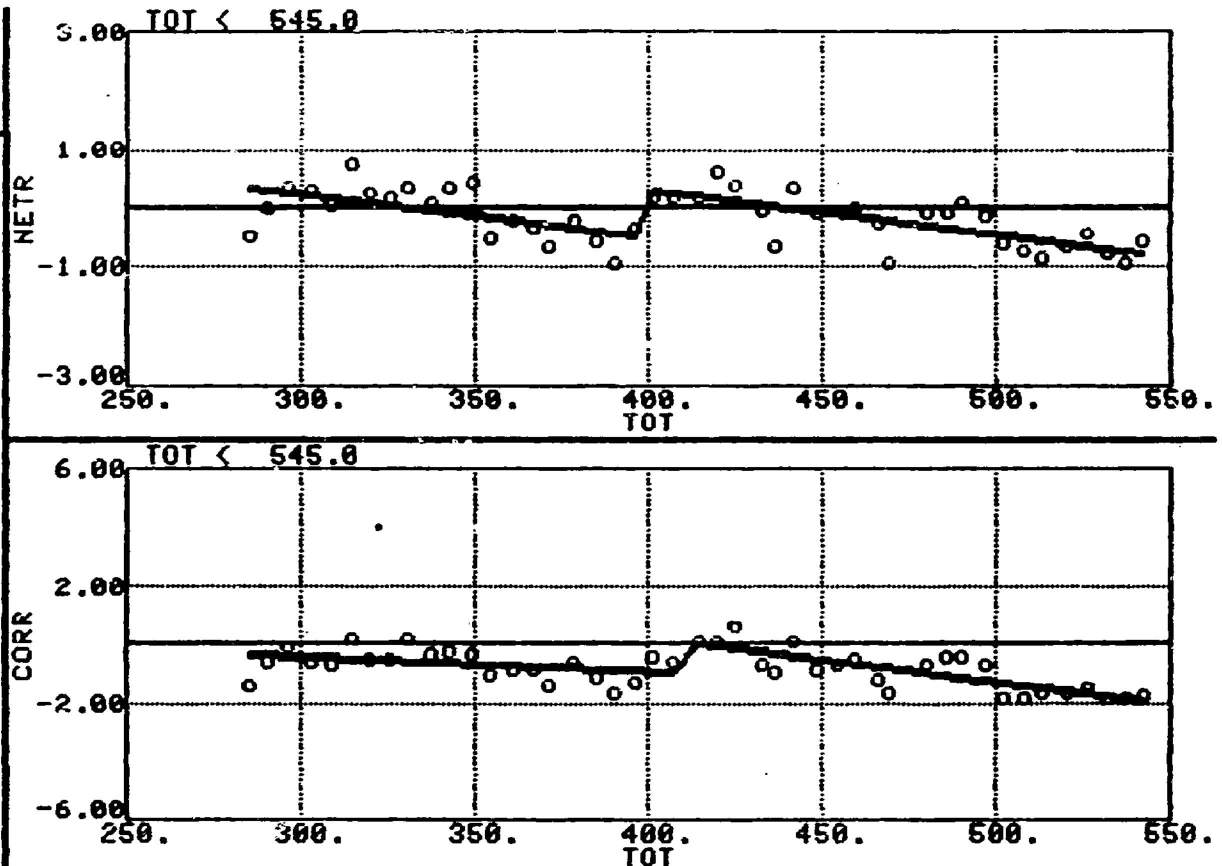

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Figure 5.10 Health Indices for E5237

ENGINE PROFILE
MYRTLE BEACH AFB

E5237
0554L

STATUS	FMC
PACER ITEM	452/6800 C (HPT BLD)
NET CPA	100.0 %
TAT I	56
TAT II	636
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	1.8/ 6.0EFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	691.9 HRS
CYCLES	452 C (810L)

DIAGNOSTICS

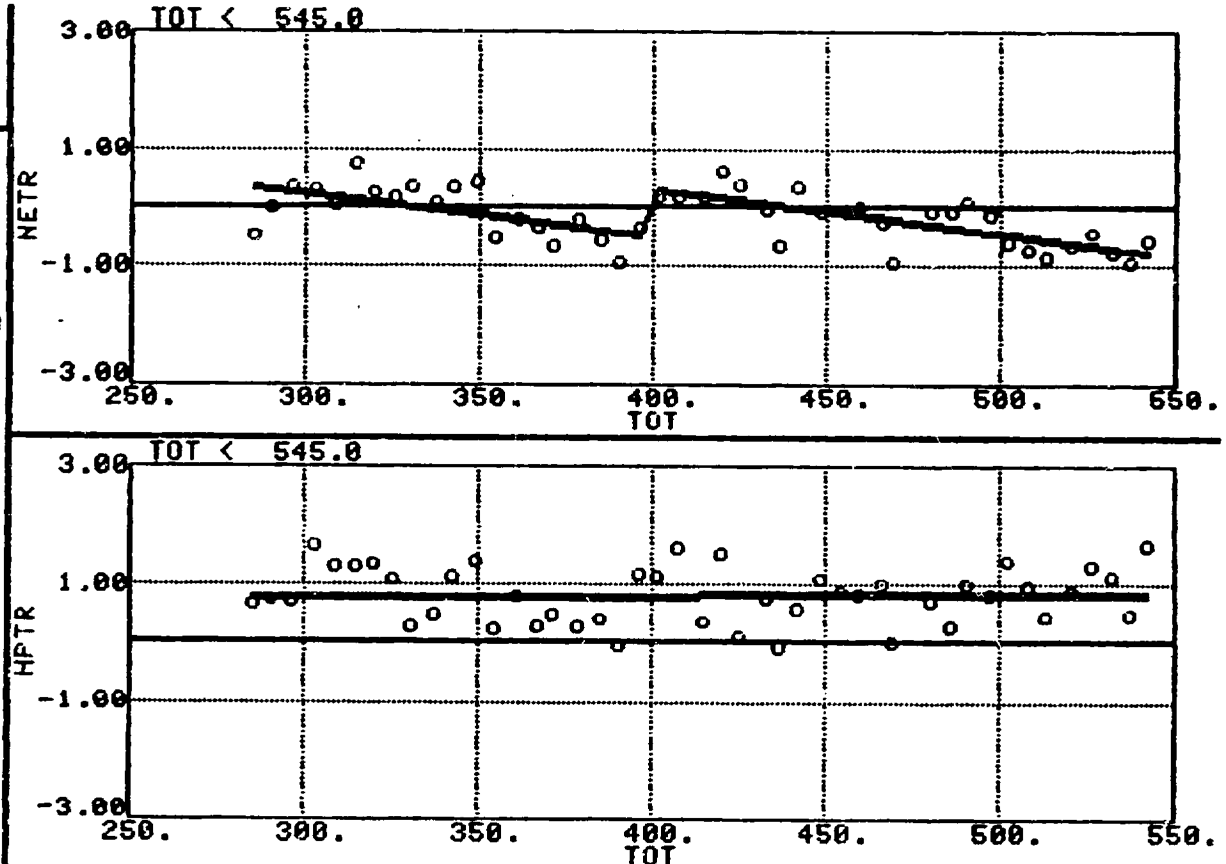

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Figure 5.10 (Continued)

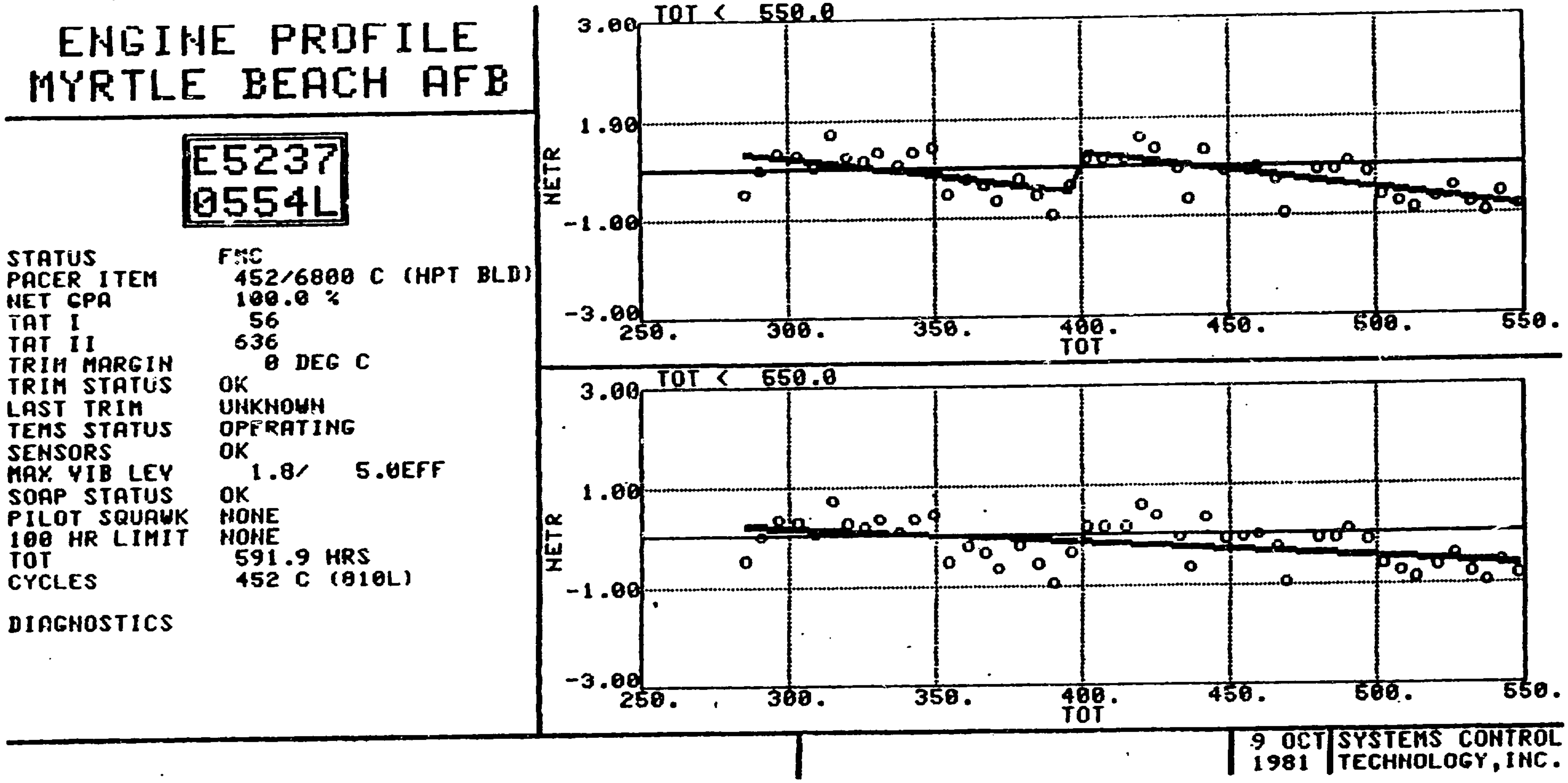

Figure 5.11 Short- vs. Long-Term Trends

ENGINE PROFILE
MYRTLE BEACH AFB

E5226
0552R

STATUS	FMC
PACER ITEM	693/6800 C (HPT BLD)
NET GPA	100.0 %
TAT I	131
TAT II	603
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.6/ 5.0EFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	866.8 HRS
CYCLES	693 C (610L)

DIAGNOSTICS

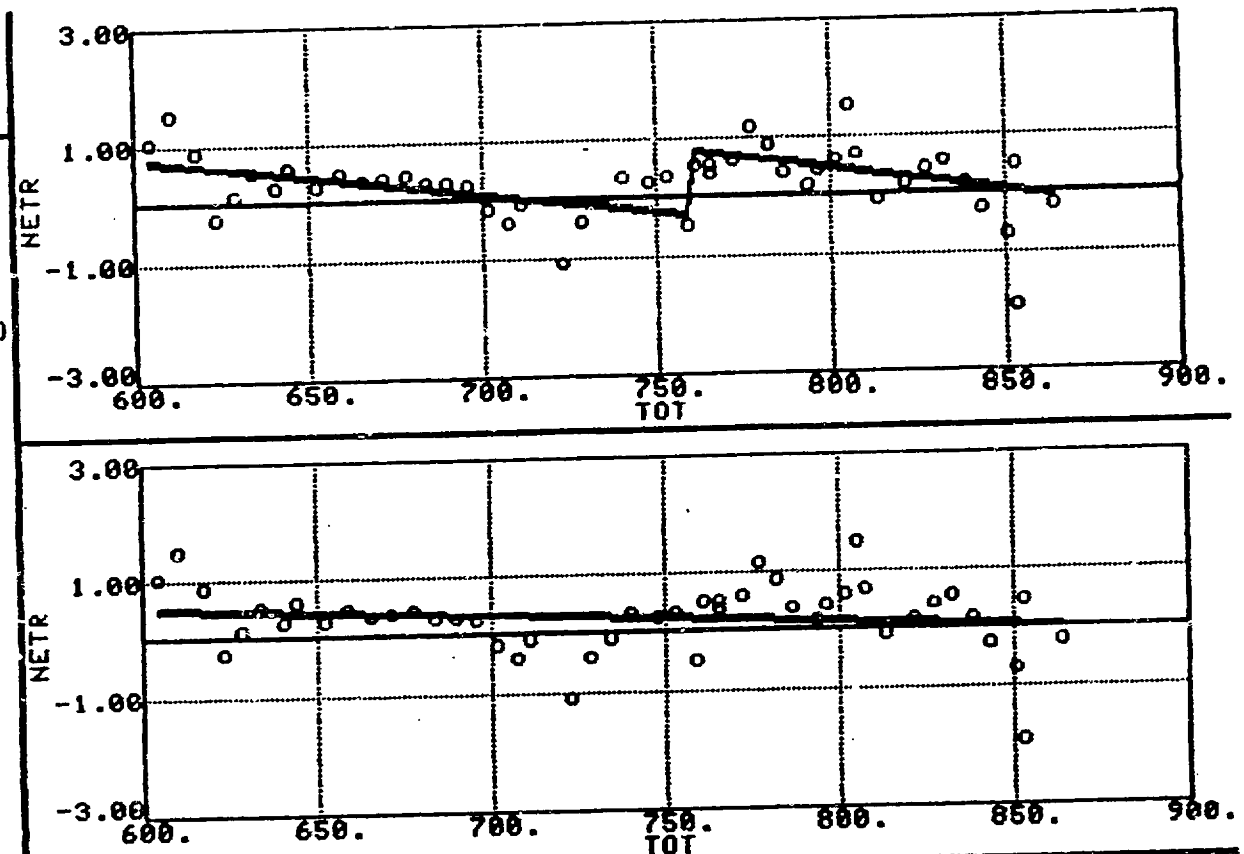

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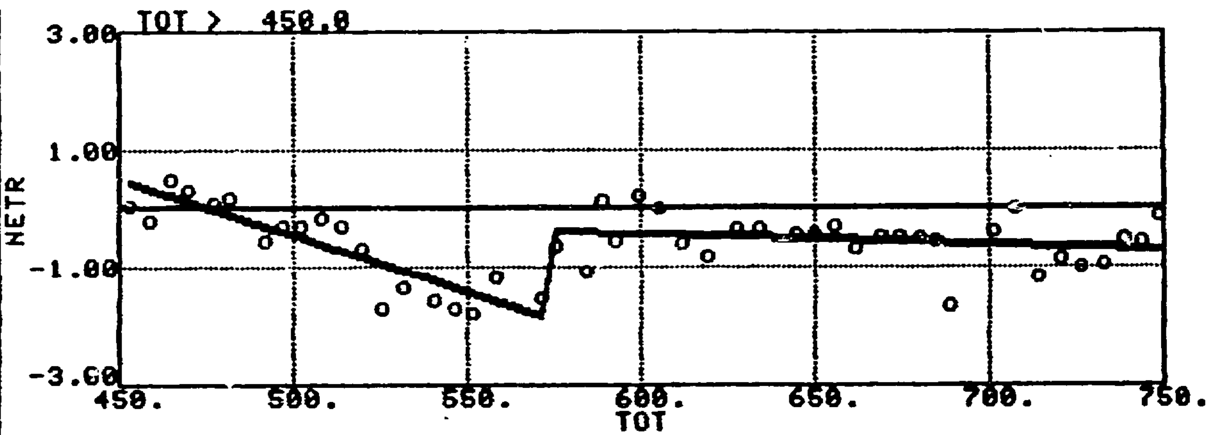
Figure 5.11 (Continued)

ENGINE PROFILE
MYRTLE BEACH AFB

E5186
0528R

STATUS	FMC
PACER ITEM	637/6800 C (HPT BLD)
NET GPA	100.0 %
TAT I	142
TAT II	658
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.5/ 5.0FFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	751.1 HRS
CYCLES	637 C (810L)

DIAGNOSTICS



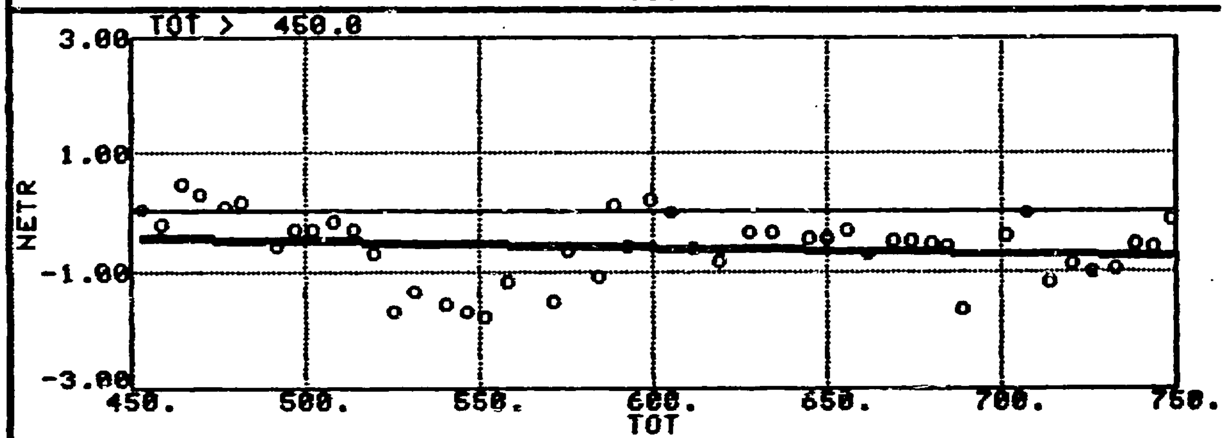


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Figure 5.11 (Continued)

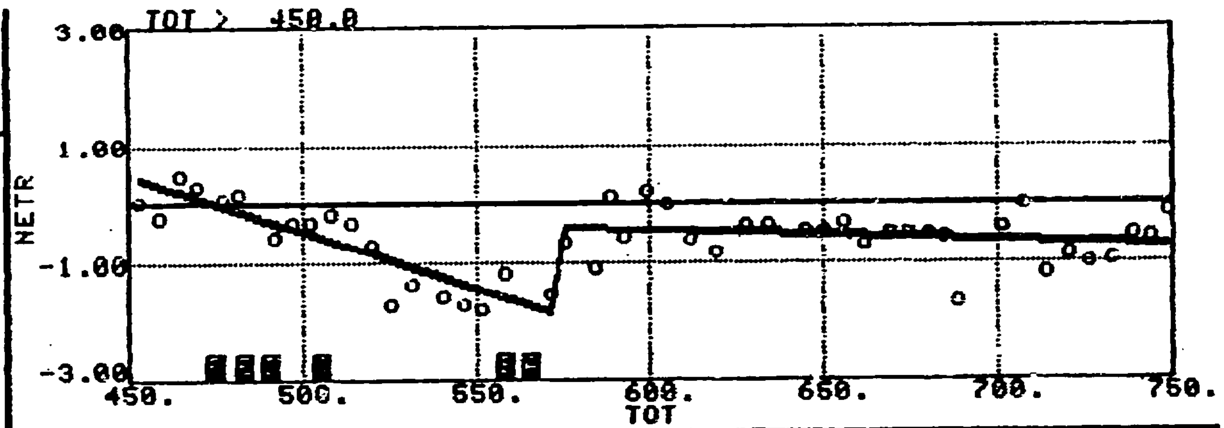
Correlations between significant maintenance actions and improvements in the net engine rating are shown in Figure 5.12. One engine, 5240, has no significant maintenance actions and a plot of NETR shows only a slow, gradual decline.

ENGINE PROFILE
MYRTLE BEACH AFB

E5186
0528R

STATUS	FMC
PACER ITEM	637/6800 C (HPT BLD)
NET GPA	100.0 %
TAT I	142
TAT II	658
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.5/ 5.0FFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	761.1 HRS
CYCLES	637 C (810L)

DIAGNOSTICS



MAINTENANCE HISTORY

A: 79190/1-ENGINE WATER WASH.

D: 79128/4-INTERNAL FAILURE OF T5 AMPLIFIER CONTROL.
ITEM REMOVED & REPLACED.

D: 79128/3-INTERNAL FAILURE OF T5 AMPLIFIER CONTROL.
FAULTY ITEM REMOVED.

D: 79128/2-INTERNAL FAILURE OF T5 AMPLIFIER CONTROL.
ITEM REMOVED & REPLACED.

F: 79059/1-F.O.M. REMOVAL OF TURBINE ENGINE.
FAULTY ITEM REMOVED.

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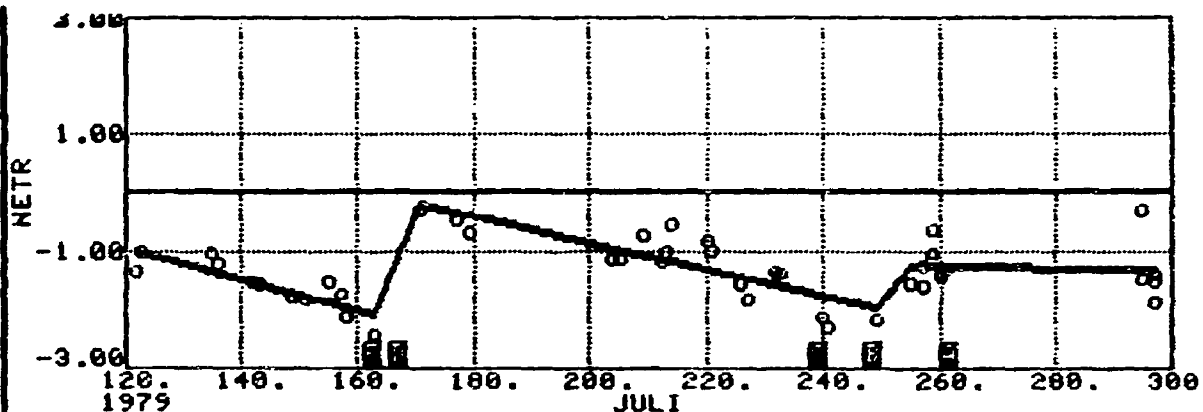
Figure 5.12 Net Engine Rating With Maintenance Correlation

ENGINE PROFILE
MYRTLE BEACH AFB

E5212
0536R

STATUS	FMC
PACER ITEM	887/6800 C (HPT BLD)
NET CPA	100.0 %
TAT I	194
TAT II	778
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	2.6/ 6.0FFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	1064.5 HRS
CYCLES	887 C (810L)

DIAGNOSTICS



MAINTENANCE HISTORY

B: 79250/1-F.O.M. REMOVAL OF FAN STATOR VANE.
ITEM REMOVED & REINSTALLED.
D: 79169/1-ENGINE WATER WASH.

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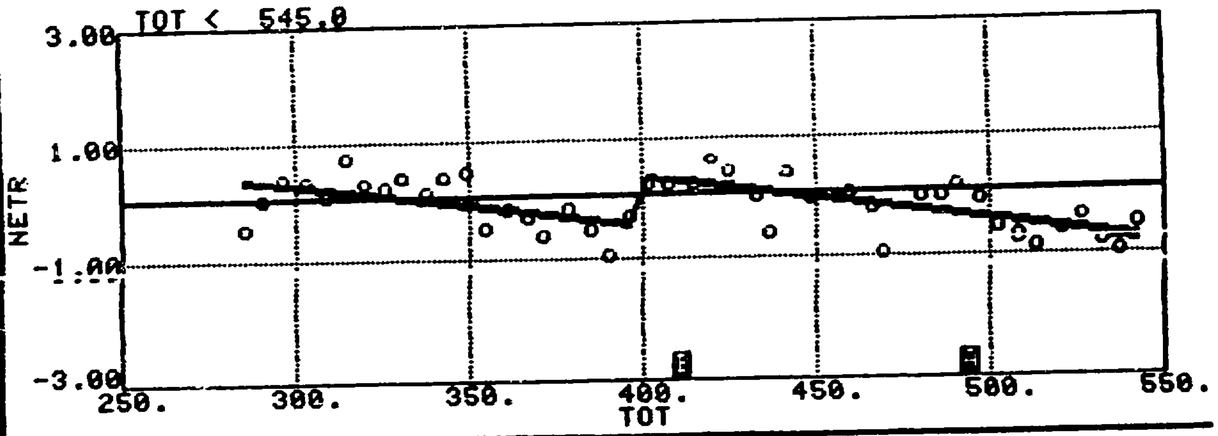
Figure 5.12 (Continued)

ENGINE PROFILE
MYRTLE BEACH AFB

E5237
0554L

STATUS	FMC
PACER ITEM	452/6800 C (HPT BLD)
NET CPA	100.0 %
TAT I	56
TAT II	636
TRIM MARGIN	0 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	1.8/ 6.0EFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	591.9 HRS
CYCLES	452 C (810L)

DIAGNOSTICS



MAINTENANCE HISTORY

A: 79279/1-F.O.M. REMOVAL OF QUAD ENGINE CONTROL.
ITEM REMOVED & REPLACED.

B: 79194/1-ENGINE WATER WASH.

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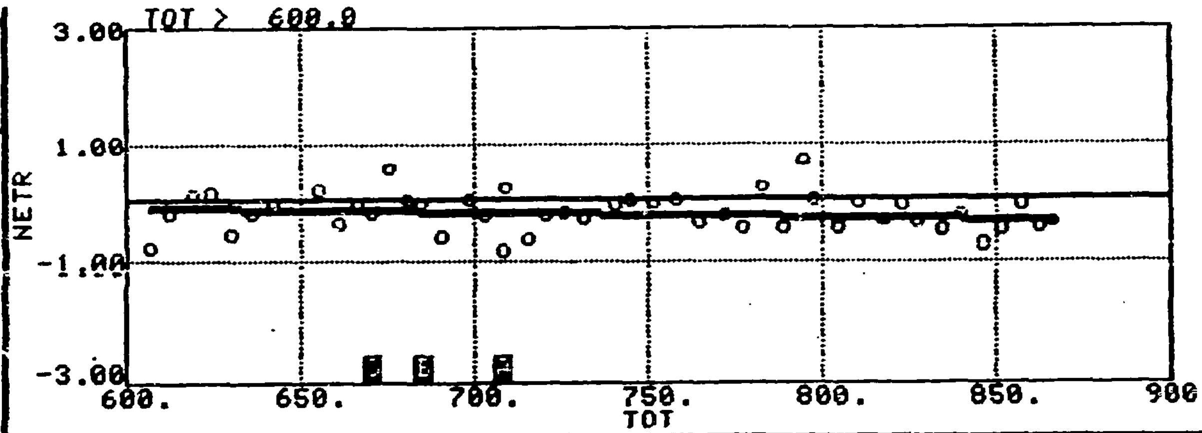
Figure 5.12 (Continued)

ENGINE PROFILE
MYRTLE BEACH AFB

E5240
0178R

STATUS	FMC
PACER ITEM	684/6800 C (HPT BLD)
NET CPA	100.0 %
TAT I	5
TAT II	657
TRIM MARGIN	6 DEG C
TRIM STATUS	OK
LAST TRIM	UNKNOWN
TEMS STATUS	OPERATING
SENSORS	OK
MAX VIB LEV	1.8/ 5.0FFF
SOAP STATUS	OK
PILOT SQUAWK	NONE
100 HR LIMIT	NONE
TOT	866.7 HRS
CYCLES	684 C (810L)

DIAGNOSTICS



MAINTENANCE HISTORY

NO SIGNIFICANT 349 ENTRIES WITHIN RANGE OF PLOTTED DATA.

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Figure 5.12 (Continued)

VI. APPLICATION TO F15/F100 EDS FLIGHT TEST DATA

6.1 INTRODUCTION

Chapter VI presents a discussion of the activities at SCT in the application of thermodynamic cycle monitoring to F15/F100 EDS flight test data. Test background is provided and a discussion of analysis techniques and results is pursued. As explained in earlier chapters, the success of a thermodynamic cycle monitoring algorithm is dependent on the quantity and quality of the data which are processed. With early phases of the flight test, insufficient amounts of data were available. Consequently, activities at SCT were directed towards improving the data acquisition logic of the EDS and analyzing the existing data to improve its repeatibility. Therefore, discussion of analysis activities will proceed as follows:

- initial model development activities and data analysis
- high-power/low-power analyses
- cluster analyses
- pilot option/automatic take-off record analyses
- conclusive model development and reduction of parameters to module-directed indices

6.2 TEST BACKGROUND

The EDS flight evaluation was conducted at Langley AFB, Virginia, from April 1980 through June 1981. This evaluation was conducted in three phases: the debug phase, the flight evaluation phase, and the extended flight evaluation phase (see Table 6.1). Five F15 aircraft and eleven F100 engines from the 1ST Tactical Fighter Wing, were equipped with the EDS. During the evaluation, nearly 1100 sorties, encompassing almost 1400 aircraft flight hours (AFH) and 2700 engine flight hours (EFH) were generated with the EDS aircraft/engines. Over 4100 engine operating hours (EOH) were accrued on the

Table 6.1

EDS Flight Evaluation Phase [45]

PHASE	DATES FROM	TO
DEBUG	1 APRIL 1980	31 AUG 1980
FLIGHT EVALUATION	1 SEPT 1980	12 DEC 1980
EXTENDED FLIGHT EVALUATION	13 DEC 1980	28 JUNE 1981

eleven EDS engines. Summaries of the aircraft and engine flight statistics are provided in Tables 6.2 and 6.3 [45].

The objectives of the test were to evaluate [46]:

- automatic time/cycle data recording and transfer to MMICS
- validity of fault detection and isolation of EDS
- ability of AF personnel to maintain EDS
- the ability of EDS to acquire in-flight data automatically for use in engine trending and engine performance/trim status
- the supportability of EDS
- life cycle cost parameters including secondary damage reduction resulting from early detection of requirements for maintenance actions
- the ability of EDS to meet the 31 TAC/AFLC requirements
- EDS ground equipment units as aircraft flight support equipment

A brief description of the EDS is now provided with a summary of the amount and type of data which were collected, and some specific observations of the test experience.

The EDS system uses a series of engine transducers mounted in conveniently located positions in the gas path. The engine, as well as lubrication and fuel distribution systems, is monitored to detect out-of-limit behavior. Subsystem variables are sampled continuously by an engine-mounted, fuel-cooled microprocessor system, the engine multiplex (EMUX). This processor is connected via a data bus to an airframe-mounted avionics computer dedicated to the EDS, the data processing unit (DPU). The DPU stores data consisting of time histories of key engine variables before, during, and after an event is detected. These data are later recoverable for general analysis to isolate faulty behavior.

In addition to fault information, steady-state data are acquired in flight for performance and trend checks. These data "points" are recorded when aircraft and throttle states have not changed significantly for a predetermined settling period.

Table 6.2

EDS Aircraft Flight Statistics [45]

AIRCRAFT TAIL NO.	DEBUG	SORTIES/AFH FLIGHT EVALUATION	EXT. FLT. EVALUATION	TOTAL
74-099	30/34.6	68/92.2	121/150.4	219/277.2
74-103	115/136.9	39/51.7	1/1.1*	155/189.7
74-105	71/88.9	43/58.6	102/127.7	216/275.2
74-107	118/147.7	73/103.8	94/111.5	285/363.0
74-108	38/47.6	76/92.8	103/125.3	217/265.7
	372/455.7	299/399.1	421/516.0	1092/1370.8

* Sent to Warner Robbins AFB for Major Airframe Repair In December 1980.

Table 6.3

EDS Engine Flight Statistics [45]

ENGINE S/N	DEBUG	SORTIES/EFH/EOH FLIGHT EVALUATION	EXT. FLT. EVALUATION	TOTAL EDS	TOT*
680160	52/62.4/104.0	36/54.9/70.1	118/140.0/217	206/257.3/391.1	1664.7
680311	49/57.7/95.0	63/77.3/125.4	38/51.9/76.4	150/186.9/296.8	1575.8
680330	62/73.1/107.0	77/99.1/142.5	93/112.8/169.7	232/285.0/419.2	1369.6
680415	23/29.9/57.4	74/95.0/142.2	104/127.7/200.8	201.252.6/400.4	974.3
680470	122/152.2/254.4	40/51.9/85.4	97/120.1/176.4	259/324.2/516.2	863.6
680528	61/73.4/115.6	38/47.2/78.3	96/118.7/177.6	195/239.3/371.5	1154.4
680639	70/87.9/152.8	45/59.9/84.6	42/50.9/78.6	157/198.7/316.0	769.7
680694	115/136.9/211.4	39/50.9/82.3	39/47.5/75.0	193/235.3/368.7	1271.3
680722	58/72.5/112.2	63/84.5/126.0	0/0.0/3.0	121/157.0/241.2	906.0
680801	117/146.4/224.6	13/18.4/29.6	94/114.7/172.0	224/279.5/426.2	1252.4
680907	13/15.1/37.4	66/94.2/138.4	122/149.9/212.2	201/259.2/388.5	1065.8
	742/907.5/1471.8	554/733.3/1105.3	843/1034.2/1558.7	2139/2675.0/4135.8	

*Total Operating Time (Hours) as of 28 June 1981

Data acquired by the DPU for performance and trend consist of several samples which are processed to remove noise and are stored. After a flight, the data generated in flight are passed to one of two portable units, the data collection unit (DCU), or the data display unit (DDU) for remote processing. The DDU is used for engine troubleshooting and trim. It is connected when trouble flags apper in the DPU panel. The DCU is used under normal conditions to retrieve stored data for trending and analysis. These data are made available to a flight test dedicated ground station computer for on-site processing or off-base transfer to a central facility. A schematic of the data collection process is shown in Figure 6.1.

The data acquisition windows for the EDS are as follows:

- performance*
- trend/stable*
- trim/ground run
- pilot option
- diagnostic events

* recording is inhibited in the case of an exceedance

Based on the data collected between 1/3 and 1/12/80, EDS system reliability is summarized below [47]:

	HITS	GOODS	FALSE II	FALSE I	MISSES	ACCURACY
TOTAL:	63	1006	6	3	0	99.7

(The reliability criteria used here are the same as those applied in the evaluation of the A10/TF34 TEMS.)

During the course of the flight evaluation, several problems were experienced in the acquisition of the data records. Problems involved the rate and power setting at which the data were acquired. As the Flight Test Program progressed, new data sets were sent to SCT for analysis. The initial data set transmitted contained an insufficient amount of trending data. During the first nine months of the program, a trending data acquisition rate of 10 per 100 EOH was experienced, while in the next three months, a rate of 2

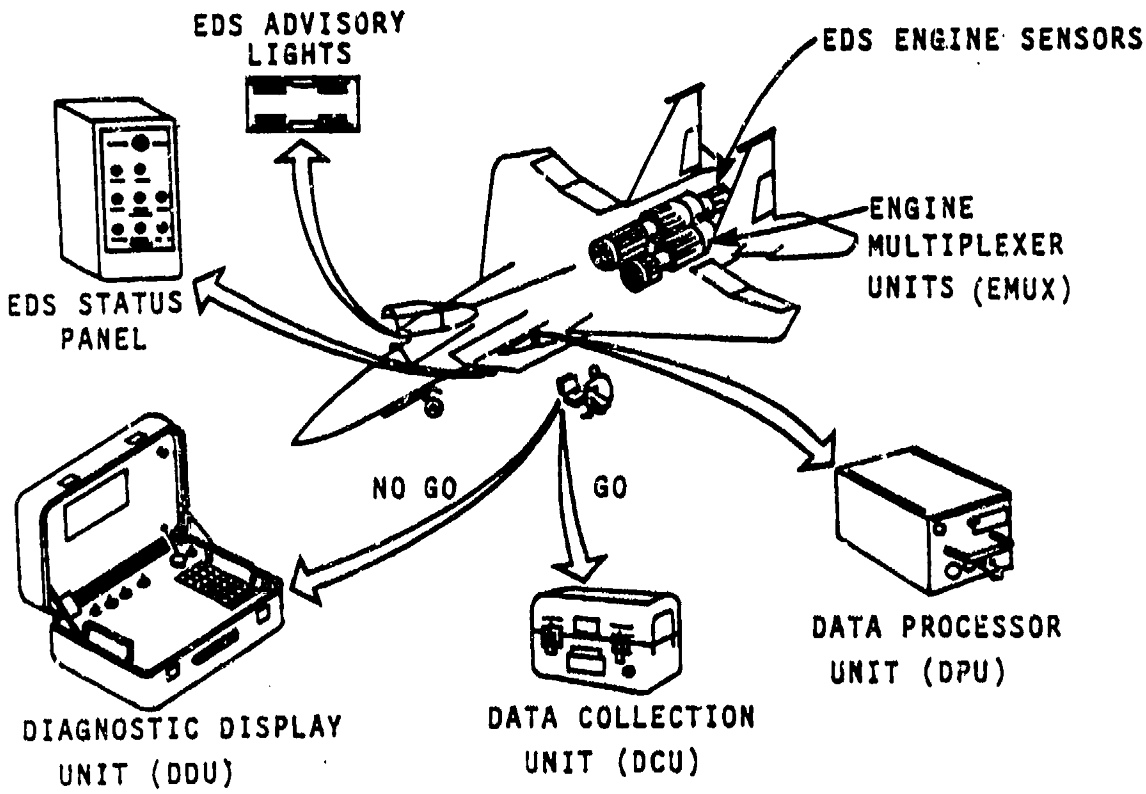

Figure 6.1 EDS Data Collection

per 100 EOH was experienced. These rates are small when compared to the A10/TF34 TEMS rate of 35 per 100 EOH. Late in the evaluation, several changes were made to the EDS software and an additional, quasi-stabilized (i.e., take-off) trending record was added. After these changes were made, acceptable data acquisition, from both a rate and power setting standpont, was realized.

A summary of the data record transmittals from Langley AFB in St. Louis to the CYBER 175 computer at the WPAFB is given in Table 6.4. In addition to the usage, trend, performance check, and take-off records, an automated EDS maintenance record file was to have been transmitted. Because of changes in the contractual responsibilities of maintenance personnel during the course of the program, maintenance records were sent with only 20 percent of the transmittals.

6.3 MODEL DEVELOPMENTS

The initial baseline models which were developed reflect the paucity of EDS data in the early part of the program. Using the methods which were applied to TEMS data, but without tightly windowing the data, baseline models were created. Tables 6.5 and 6.6 present initial model development results. The large baseline model standard deviations can be attributed to two factors: the scarcity of data and the flight conditions for which the data were collected. Large differences between flight data model statistics and deck model statistics are attributable to many factors, the most outstanding being that the portions of the flight envelope from which EDS data were gathered were inconsistent with status deck flight conditions. This is illustrated in Table 6.5.

With the second and third data set transmittals, new versions of the baseline models were developed. Data were screened using the previously developed models. It can be seen in Table 6.7 that with each successive model, the standard deviations showed improvement. Model errors were not only attributable to data scarcity, but to the fact that the data are not uniformly scattered, and that with early data transmittals, data are clustered mainly in

Table 6.4

Record Transmittal Summary By Engine Serial Number [45]

ENGINE S/N	USAGE RECORDS	TREND RECORDS	PERF. CHK. RECORDS	TAKEOFF RECORDS
P60160	46	22	9	18
P680311	29	24	11	7
P680330	65	37	31	17
P680415	50	35	24	24
P680470	44	34	30	36
P680528	34	25	17	19
P680639	26	25	7	0
P680694	44	42	24	11
P680722	31	18	12	0
P680801	40	26	26	24
P680907	55	33	16	37
	464	321	207	193
TOTAL RECORDS = 1185				

Table 6.5

Variable Means

UNITS	VARIABLE	STATUS DECK DATA (636 POINTS)	EDS FLIGHT DATA (45 POINTS)
RPM	N1	8714	7406
RPM	N2	11,650	10,770
PS1	PT25C	29.13	24.68
^{o}C	TT2	7.428	25.09
PPH	WFPC	5203	3097
PSI	PB	208.3	146.4
^{o}C	T25C	99.35	87.02
PS1	PT6	26.47	21.78
^{o}C	TS3	311.7	340.0
^{o}C	FTIT	702.2	606.6

Table 6.6

Model Standard Deviations

UNITS	VARIABLE	STATUS DECK DATA (636 POINTS)	EDS FLIGHT DATA (45 POINTS)
RPM	N1	92	180
RPM	N2	40	250
PSC	PT25C	.13	.83
°C	TT2	1.7	4.2
PPH	WFPC	220	180
PSI	PB	1.3	6.3
°C	T25C	.97	4.8
PSI	PT6	.79	1.2
°C	TS3	1.5	11.9
°C	FTIT	13	18.0

Table 6.7

F100 Model Standard Deviations

		BASELINE MODEL			STATUS DECK MODEL
VARIABLE	UNITS	SEPT '80 MODEL	NOV '80 MODEL	JAN '81 MODEL	
T25C	°C	4.8	2.6	2.4	.97
PT25C	PSI	0.83	0.58	0.68	0.13
TS3	°C	11.9	7.6	8.3	1.5
PB	PSI	6.3	5.0	5.6	1.3
FTIT	°C	18.	13.	13.	13.
PT6	PSI	1.2	0.67	0.79	.79
N2	RPM	250.	75.	67.	40.
WF	PPH	---	160.	130.	---
NI	RPM	180.	140.	140.	92.
AJ	FT^2	---	0.54	0.45	---
MACH	---	---	0.15	0.15	---
ALT	FT	---	1100.	1100.	---
PLA	DEG	---	2.9	2.3	---
PT2	PSI	---	0.76	0.72	---
TT2	°C	4.2	1.8	1.7	1.7
RCVV	DEG	---	1.9	1.9	---

low-power regions. Discussion of analyses leading to these conclusions will now be presented.

6.4 HIGH-POWER/LOW-POWER ANALYSES

Scatter plot analyses of the two data sets which were initially transmitted indicated that the data base contained a large number of lower power points, a smaller number of high-power points, and very few intermediate power points. A histogram of 251 F100 data points (as of 2/81) by PLA range is shown in Figure 6.2. The question was raised as to whether engine data are more repeatable at high power or low power.

A methodology for evaluating data repeatability is summarized below:

- Engine model:

$$Y(X)_{SENSED} = Y(X)_{NOMINAL} + AEFF + V + W$$

Observed Sensor Reading	True Value of Y When EFF=V=W=0	Engine Health Parameter	Sensor Noise	Nonrepeatability Noise

- Further analysis yields:

$$\sigma_y^{LP} > \sigma_y^{HP} \leftrightarrow W_y^{LP} > W_y^{HP}$$

Low-Power Model Standard Deviation — High-Power Nonrepeatability Standard Deviation

- Larger model standard deviations indicate less repeatable data.

Using the data base, two subsets were created. The first data set consisted of valid high-power points ($80 \leq PLA \leq 90$), and the second set consisted of low-power points ($30 \leq PLA \leq 37$). Both sets represented a cross-section of the engines. Variances of the raw data and variances of the model residuals were compared to determine which data set was more repeatable. When this analysis was performed initially, the results indicated that high power points were more repeatable. The results in Table 6.8 show that σ_y^{LP} is significantly greater than σ_y^{HP} in many instances. However, the results were not entirely conclusive because of the scarcity of

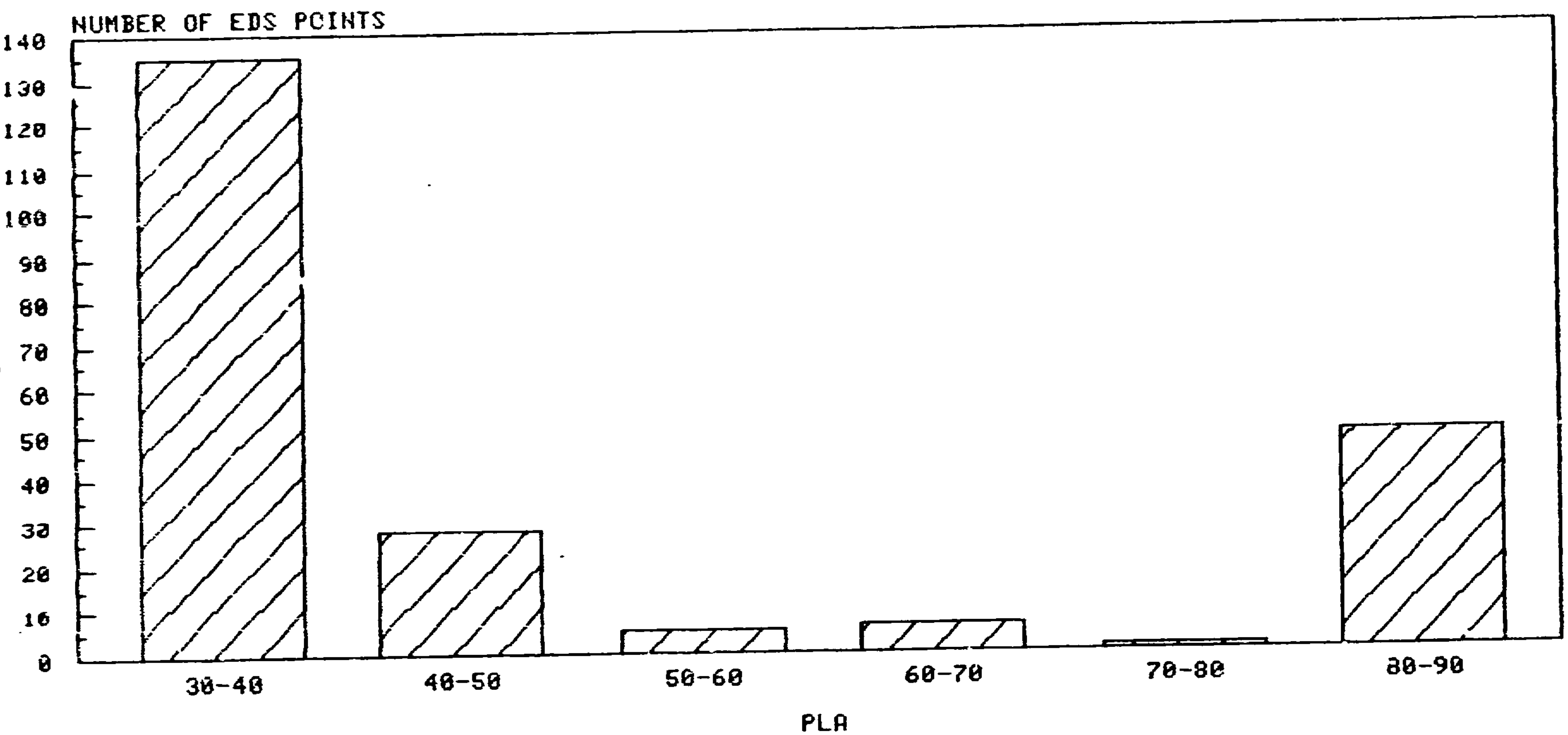

Figure 6.2 Histogram of EDS Points Versus PLA Range (251 points, as of 2/81)

Table <.8

Data Repeatability Results: Low Versus High Power Data

y	σy^{LP}	σy^{HP}
T25C	2.53	2.16
P25C	.788	.950
TS3	14.90	4.24
PB	9.68	5.38
FTIT	20.10	6.82
PT6	1.19	1.30
N2	126.00	64.90
WF	138.00	169.00

NOTE: ALL BASELINE MODELS WERE CHOSEN FROM THE BEST FITS USING 2 INDEPENDENT VARIABLES data. Changes in the EDS logic later in the program led to more high-power data being collected. The change in data distribution is shown in Table 6.9.

Results of the later analysis are shown in Tables 6.9 and 6.10. They show that since $\sigma_y^{LP} > \sigma_y^{HP}$ and the confidence intervals do not tend to overlap, high-power data appears to be more repeatable than low-power data.

6.5 CLUSTER ANALYSIS

As mentioned previously, accurate results from a gas path analysis algorithm depend on a data set which is uniformly distributed. The data which were analyzed in the early part of the program resided in clusters which did not lend themselves to accurate model development. An algorithm was developed which provided a simple and efficient method for determining where the clusters lie. Results proved to be useful in determining whether data were uniformly scattered, which points were outliers, and defining reasonable hard sensor limits for data screening.

Operation of the algorithm is as follows. The cluster routine takes as input a data array. First, the data are sorted into increasing order. Then the average distance between points is computed. Points which are many times further apart than the average are discarded as outliers. This process is repeated until no outliers remain.

Finally, the remaining points are grouped into clusters. The points are processed in increasing order. If the distance between points I and I+1 is large, point I+1 begins a new cluster. Otherwise, it is added to the present cluster and the next point is processed similarly.

A flowchart illustrating this procedure is shown in Figure 6.3, and sample results are shown in Table 6.11.

6.6 PILOT OPTION/AUTOMATIC TAKE-OFF RECORD ANALYSIS

In April of 1981, the EDS software was modified to record automatically a time history of all EDS parameters during take-off. The data consists of 18 scans giving the time history of a single take-off. The first scan is

Table 6.9

EDS Data Acquisition Results

	DATA BASE THROUGH 12 DECEMBER 1981	DATA BASE SINCE 12 DECEMBER 1981
TOTAL NUMBER OF SCANS	251	249
NUMBER OF HIGH POWER SCANS (% OF TOTAL)	59 (23%)	244 (94%)
NUMBER OF HIGH POWER SCANS WITHIN MAX AND MIN SCREENING LIMITS (% OF TOTAL)	32 (13%)	154 (62%)

Table 6.10

Data Repeatability Results - Low Versus High Power Data

Y	95% CI FOR σ_y^{LP}	95% CI FOR σ_y^{HP}	$\sigma_y^{LP} < \sigma_y^{HP}$	CONFIDENCE INTERVALS OVERLAP	$\sigma_y^{LP} > \sigma_y^{HP}$
T25C	(2.19,3.01)	(1.87,2.57)		X	
P25C	(.682, .938)	(.822,1.13)		X	
TS3	(12.9,17.7)	(3.67,5.05)			X
PB	(8.37,11.5)	(4.65,6.40)			X
FTIT	(17.4,23.9)	(5.90,8.12)			X
PT6	(1.00,1.38)	(1.12,1.55)		X	
N2	(109.,150.)	(56.1,77.2)			
WF	(119.,164.)	(146.,201)			
		TOTALS	0	4	4

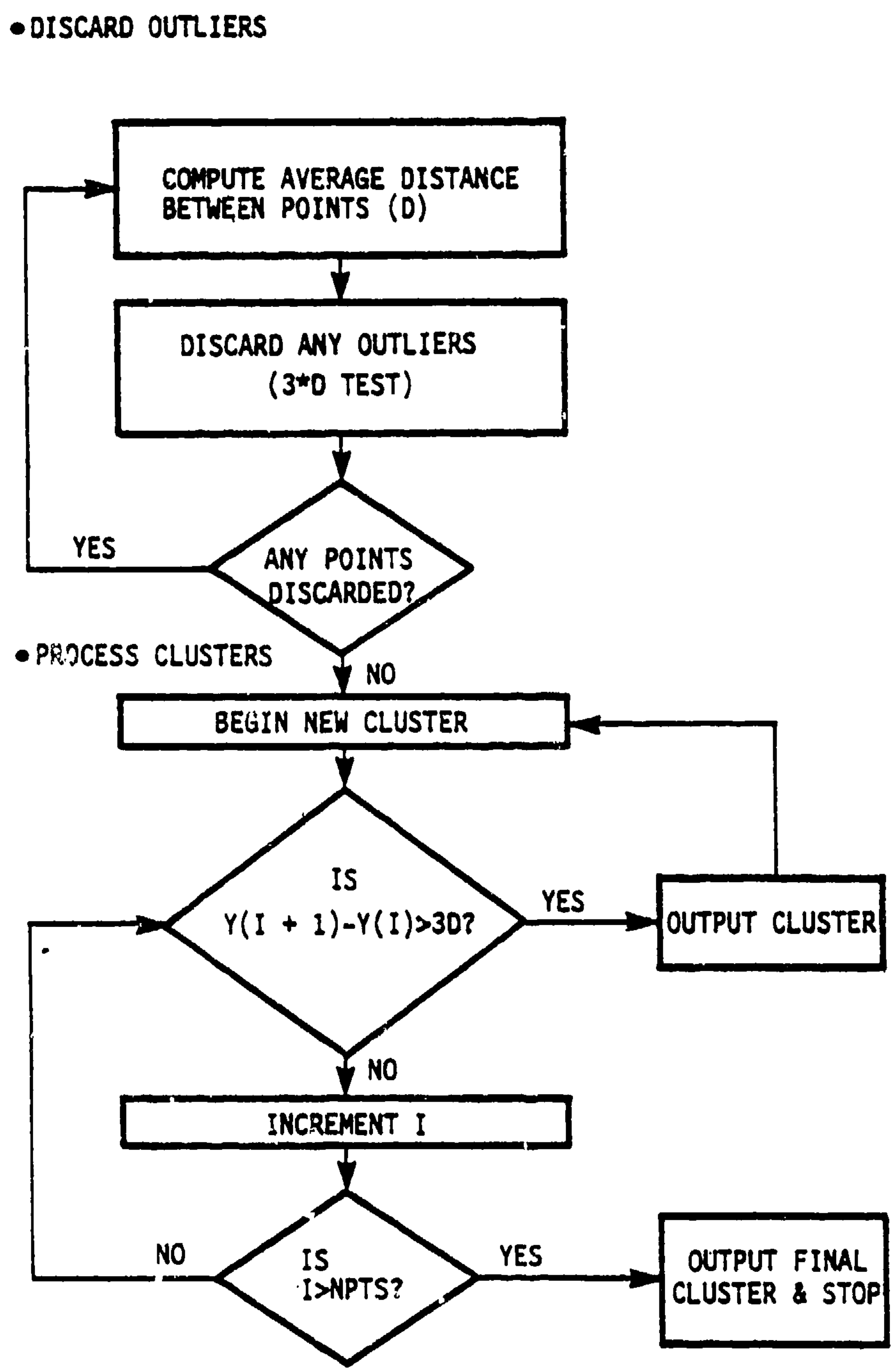

Figure 6.3 Cluster Algorithm Flowchart

Table 6.11

Sample Cluster Analysis Results

PILOT OPTION DATA, PLA CHANNEL (175 POINTS)				
OUTLIER	-.6			
CHANNEL	CLUSTER	MINIMUM	MAXIMUM	NUMBER OF POINTS
13		-16.00	89.31	174
	1	-16.00	-16.00	5
	2	15.38	17.13	5
	3	55.13	55.81	2
	4	63.56	89.31	162
EDS DATA, PLA CHANNEL (500 POINTS)				
OUTLIER	0.0	115.3	582.1	
CHANNEL	CLUSTER	MINIMUM	MAXIMUM	NUMBER OF POINTS
13		15.88	125.13	427
	1	15.88	19.56	4
	2	30.06	48.25	166
	3	51.94	93.56	310
	4	104.19	104.50	3
	5	108.38	112.94	8
	6	118.44	121.06	4
	7	124.31	125.13	2

recorded 4.5 seconds before weight off wheels, and the last scan is recorded 1.0 second after weight off wheels.

Sample take-off scans are shown in Figure 6.4. Two representative plots are shown for T25C. In mathematical notation, the plot shows $y(t_i)$ versus $t_i (i=1,2,\ldots,18)$, where

$$t_1 = -4.5, \quad t_2 = -3.5, \quad \ldots, \quad t_{18} = 1.0$$

and y is T25C, a representative operating variable. The plot shows that the variable increases approximately linearly during the 5.5 seconds in which it is recorded.

The change in y at time t_i from its initial value $y(t_1)$ is defined as $\Delta y(t_i) = y(t_i) - y(t_1)$. Figure 6.5 shows plots of $\Delta y(t_i)$ versus $t_i (i=1,2,\ldots,18)$ for T25C and represents 50 take-offs.

The plot in Figure 6.6 shows a statistical summary of the delta y values for 175 take-offs. For each operating variable, there are three superimposed plots:

$$\text{Mean } [\Delta y(t_i)] \text{ versus } t_i \qquad (1)$$

$$\text{Mean } [\Delta y(t_i)] + \sqrt{\text{Var } \Delta y(t_i)} \text{ versus } t_i \qquad (2)$$

$$\text{Mean } [\Delta y(t_i)] - \sqrt{\text{Var } \Delta y(t_i)} \text{ versus } t_i \qquad (3)$$

where the means and variances are computed from the 175 take-offs. To summarize, Figure 6.6 shows the average time history of delta y and the scatter about this average. This plot indicates that mean $[\Delta y(t_i)]$ apears to be a linear function of t_i.

Tables 6.12 and 6.13 give standard statistical summaries and cluster analysis results for the EDS data base (500 points) and the new pilot option data base (175 points). No data screening was done for this analysis. Comparison of the standard deviations of the operating variables in Tables 6.12 and 6.13 shows that the scatter is smaller for the pilot option data. This results primarily from the smaller power range occurring during take-offs.

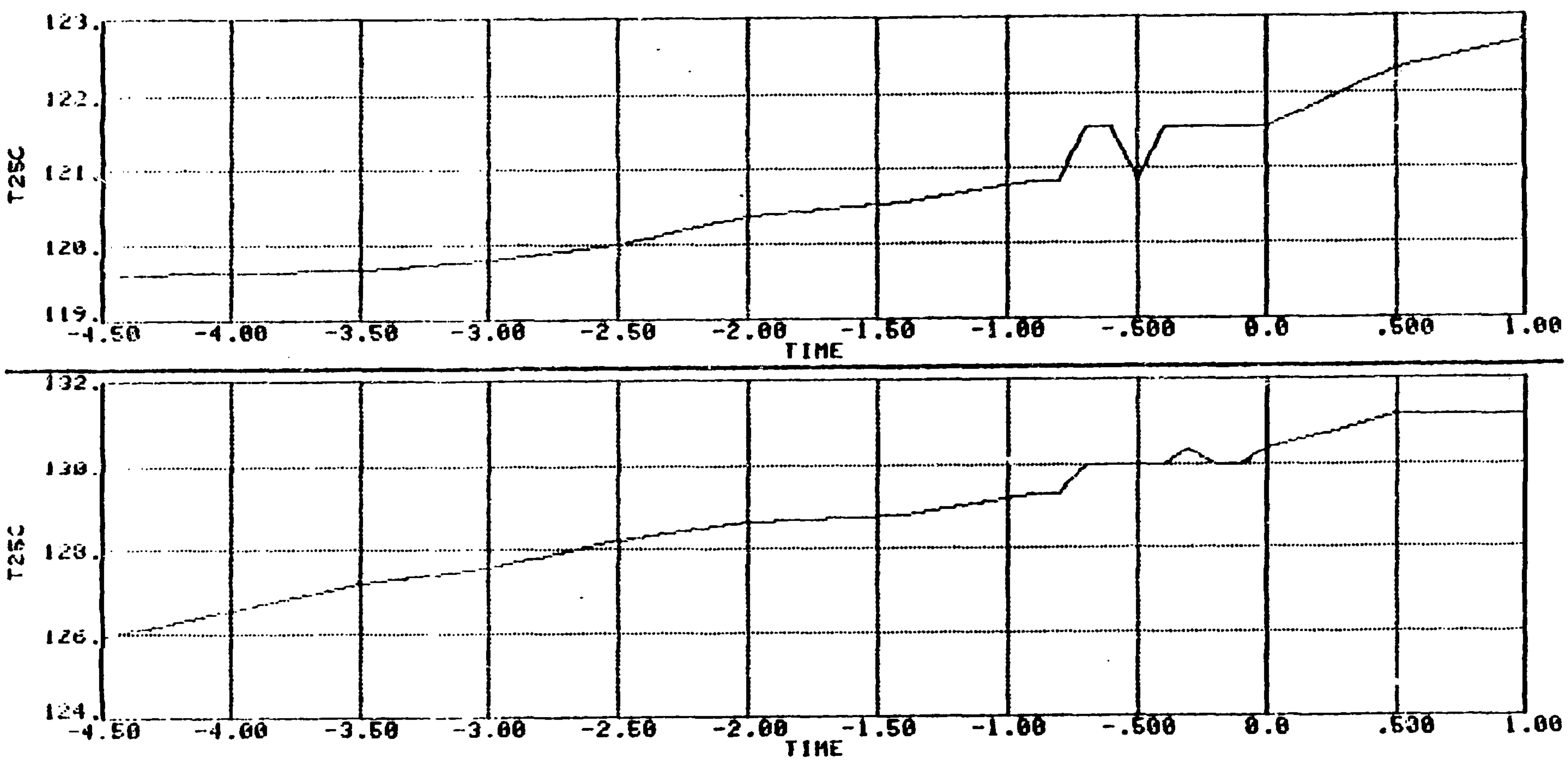

Figure 6.4 Sample Pilot Option Scans: T25C

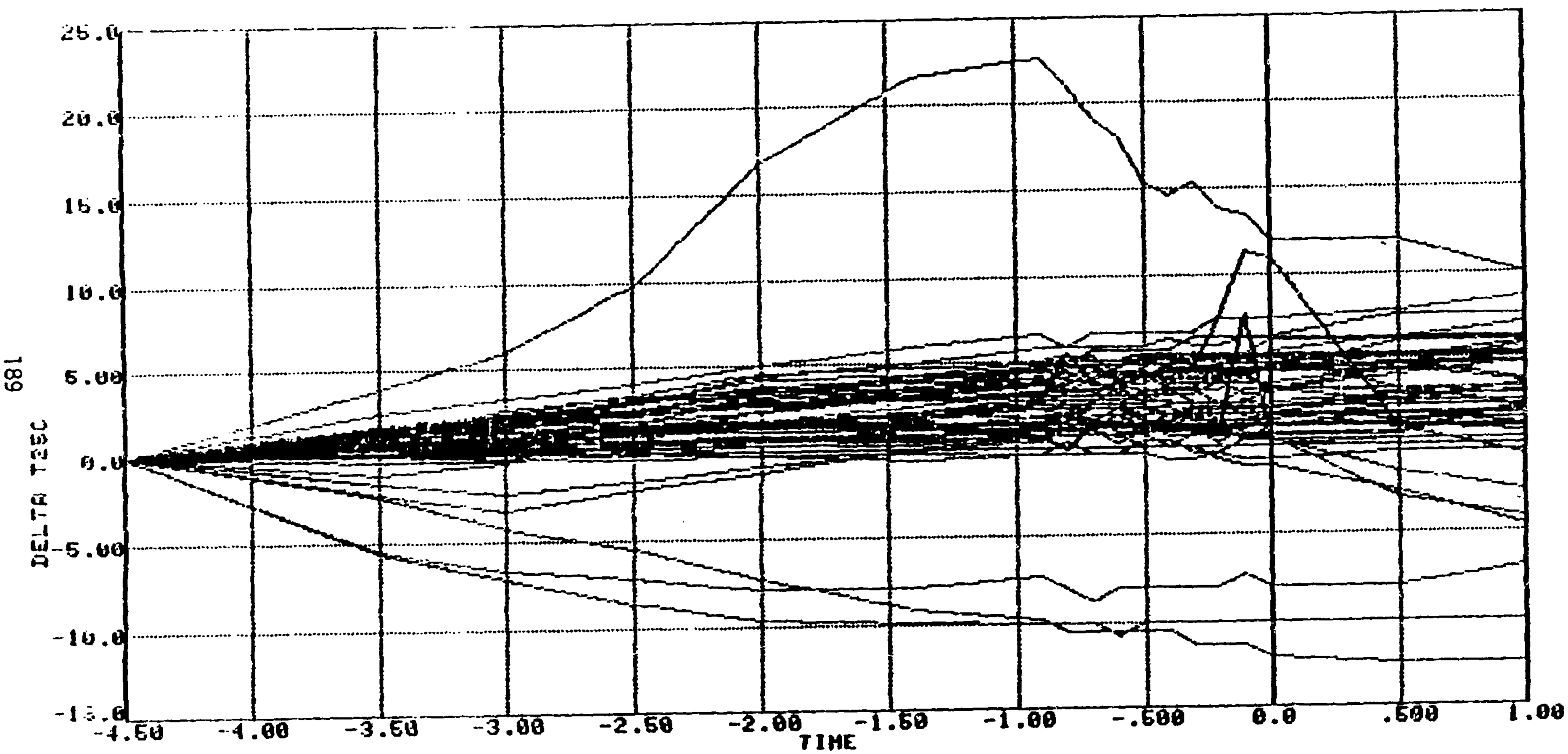

Figure 6.5 Delta T25C: 50 Scans

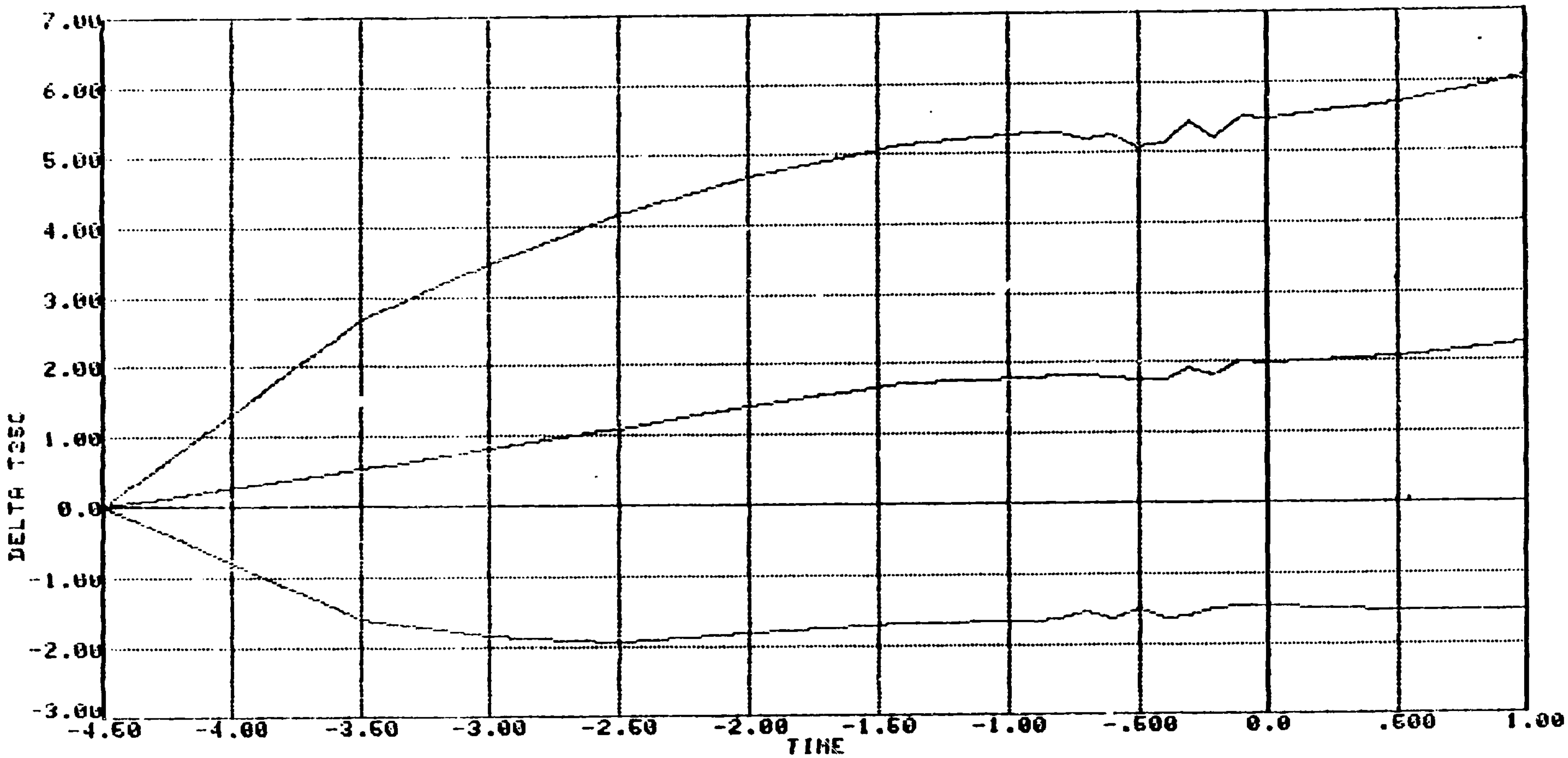

Figure 6.6 Delta T25C: Mean and CI

Table 6.12

Statistical Summary of EDS Data Base (500 Points)

CHANNEL	NAME	MINIMUM	MEAN	MAXIMUM	STD. DEV.
1	T25C	-32.13	170.70	812.38	184.38
2	P25C	16.79	31.88	344.70	18.14
3	TS3	.03	429.28	726.85	92.76
4	PB	0.00	218.85	1689.59	134.54
5	FTIT	0.00	774.64	1242.25	168.29
6	PT6	-93.29	26.47	117.65	10.10
7	N2	0.00	11880.93	12873.00	1134.15
8	WF	43.45	8807.30	97370.29	14729.64
9	N1	0.00	8839.85	16102.00	1519.14
10	AJ	0.00	3.19	6.50	.68
11	MACH	0.00	.57	1.22	.25
12	ALT	-2.50	9808.01	34622.50	8743.07
13	PLA	0.00	67.62	582.06	33.46
14	PT2	0.00	12.90	25.27	2.69
15	TT2	-15.56	31.45	4091.25	183.41
16	RCVV	-38.88	-1.08	16.00	8.43

Table 6.13

Statistical Summary of EDS Pilot Option
(Takeoff Data Time t_1 = .4.5 Seconds (175 Points)

CHANNEL	VARIABLE NAME	MINIMUM	MEAN	MAXIMUM	STD. DEV.
1	T25C	-91.56	163.74	803.44	157.06
2	P25C	16.43	37.37	42.16	4.09
3	TS3	157.41	462.45	496.12	53.19
4	PB	19.81	272.84	321.88	45.17
5	FTIT	334.00	852.50	913.19	82.17
6	PT6	16.26	35.49	40.98	4.20
7	N2	3969.00	12306.00	12763.00	843.24
8	WF	190.10	9337.75	94636.14	12730.96
9	N1	3001.00	9523.18	16102.00	1491.68
10	AJ	2.80	3.05	5.57	.44
11	MACH	0.00	.16	.63	.06
12	ALT	-1280.00	-30.50	7505.00	842.93
13	PLA	-16.00	73.51	89.31	20.53
14	PT2	13.70	14.16	15.11	.27
15	TT2	.38	15.69	29.88	5.67
16	RCVV	-42.13	3.08	16.00	8.03

Several data sets were generated to compare the repeatability of the take-off data to the other F100 data. The three data sets are:

1: take-off data collected at $t_1 = 4.5$ seconds

2: low-power EDS data ($30 \leq PLA \leq 40$)

3: high-power EDS data ($80 \leq PLA \leq 90$)

All data sets were screened for hard and soft sensor failures, thus they are comparable sets of "clean" data.

The residual (model) standard deviations for these data sets are compared in Table 6.14. Significantly smaller model standard deviations indicate more repeatable data. The low-power data set appears to be the least repeatable, while the repeatability of the take-off and high-power data are comparable. Although the engine is not in equilibrium during take-offs, the data collected is still repeatable. Hence, the take-off data appear to be valuable additions to the data base and can be used for gas path trending analysis.

6.7 FINAL BASELINE MODEL DEVELOPMENT, PARAMETERIZATION, AND HIGHLIGHTS OF RESULTS

Using data from the first 13 McAir data tapes (for period of 4/16/80 to 5/15/81), the final F100 baseline model was developed. The data were screened according to the limits shown in Table 6.15. Points with PLA less than 60 degrees or greater than 90 degrees were discarded. Also discarded were the points with one or more sensor failures, as determined by the previous baseline model. The resulting data set consisted of 112 valid high-power data scans.

Polynomial regression equations for 16 F100 operating variables were developed using the MODGEN computer program. Table 6.16 lists the independent variables which were chosen for each of the equations. Also listed in Table 6.16 are the resulting model standard deviations.

Figures 6.7 and 6.8 show selected residual plots created from the final baseline model and the 112 point high-power data set. As with earlier results, no marked trends are discernible from the residuals. This is an

Table 6.14

Comparison of Model Standard Deviations Data Set Number

y	1	2	3
T25C	3.8	2.5	2.2
P25C	.74	.79	.95
TS3	5.9	15	4.2
PB	6.6	9.7	5.4
FTIT	14	20	6.8
PT6	1.2	1.2	1.3
N2	85	130	65
WF	280	140	170
	TAKEOFF DATA AT t_1	LOW POWER EDS DATA	HIGH POWER EDS DATA

NOTE: ALL BASELINE MODELS WERE CHOSEN FROM THE BEST FIT USING 2 INDEPENDENT VARIABLES

Table 6.15

EDS Data Screening Limits

CHANNEL	VAR	LOWER LIMIT	UPPER LIMIT
1	T25C	0	180
2	P25C	14	50
3	TS3	150	600
4	PB	40	350
5	FTIT	350	1,000
6	PT6	14	45
7	N2	9000	13,000
8	WF	0	9,000
9	N1	4000	11,000
10	AJ	2.7	5.1
11	MACH	0	0.9
12	ALT	-1,000	25,000
13	PLA	-VARIABLE-	
14	PT2	5	18
15		-25	60

Table 6.16

F100 Baseline Model, June 1980

DEPENDENT VARIABLE	INDEPENDENT VARIABLES	MODEL STANDARD DEVIATION
T25C	N1,AJ,TT2	1.5
P25C	PB,AJ,RCVV,PT2*PT2	0.70
TS3	N1,PLA,TT2	5.3
PB	N1,AJ,MACH,ALT,TT2	5.9
FTIT	N1,PLA	11.6
PT6	N1,AJ,PT2,TT2*TT2	.94
N2	N1,PLA,RCVV	73.4
WF	PB,N1,AJ	163
N1	T25C,PB*PB,TT2*PT6	69
AJ	T25C,TT2,N1*N1	.052
MACH	ALT,PT2	.02
ALT	PT2,TT2,TT2*N1	2000
PLA	FTIT,PT2,PB*T25C	2.3
PT2	TT2,PB*T25C,FTIT*T25C	.27
TT2	T25C,RCVV,N2*FTIT	3.4
RCVV	N2,N1*FTIT	1.4

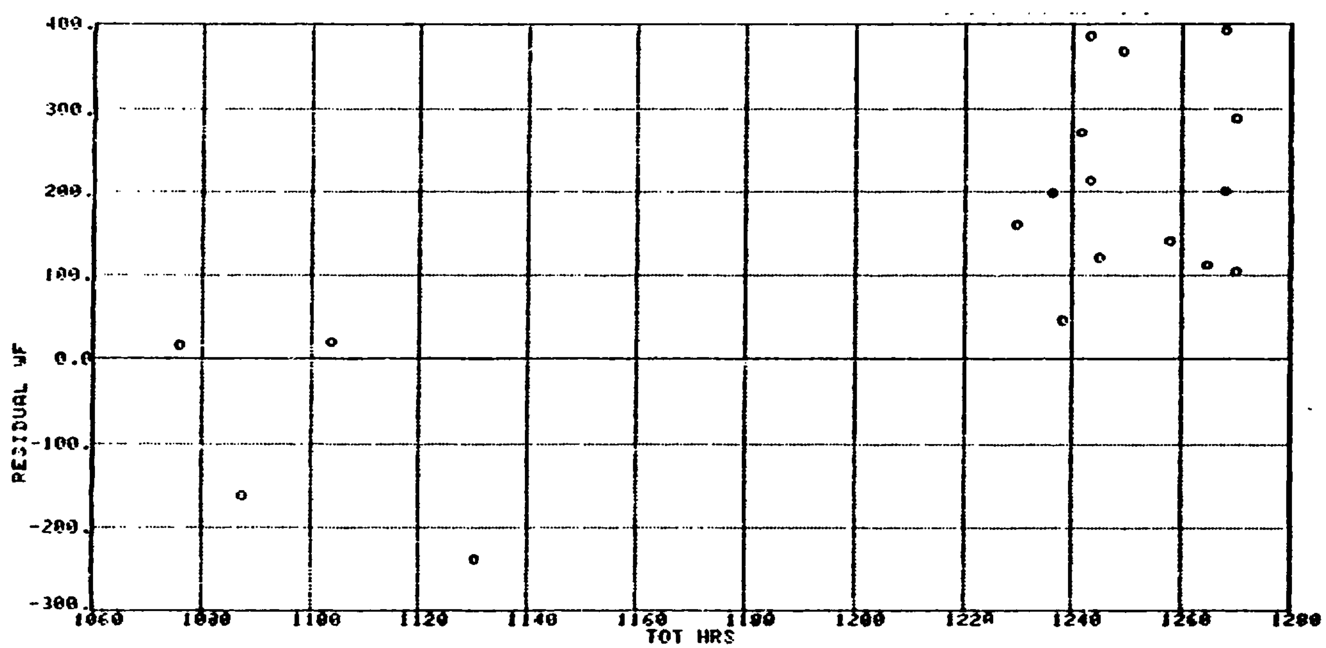

Figure 6.7 High Power EDS Data E0694: Residual WF

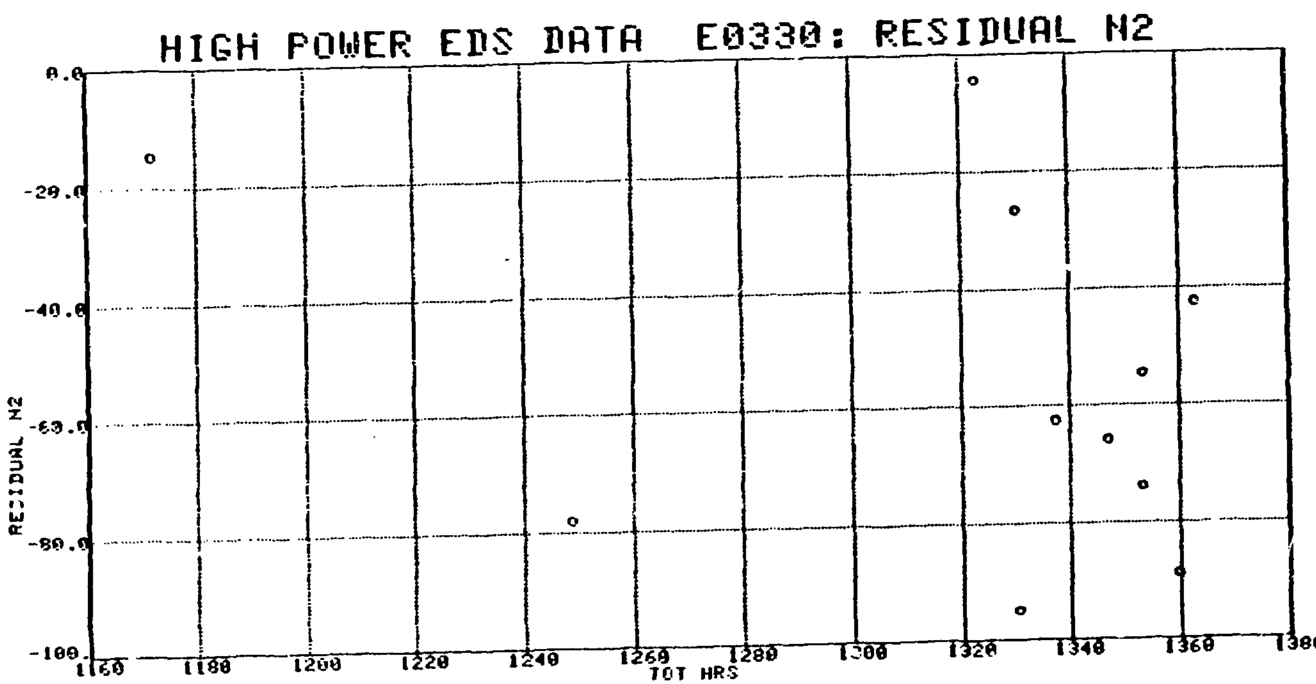

Figure 6.7 (Continued)

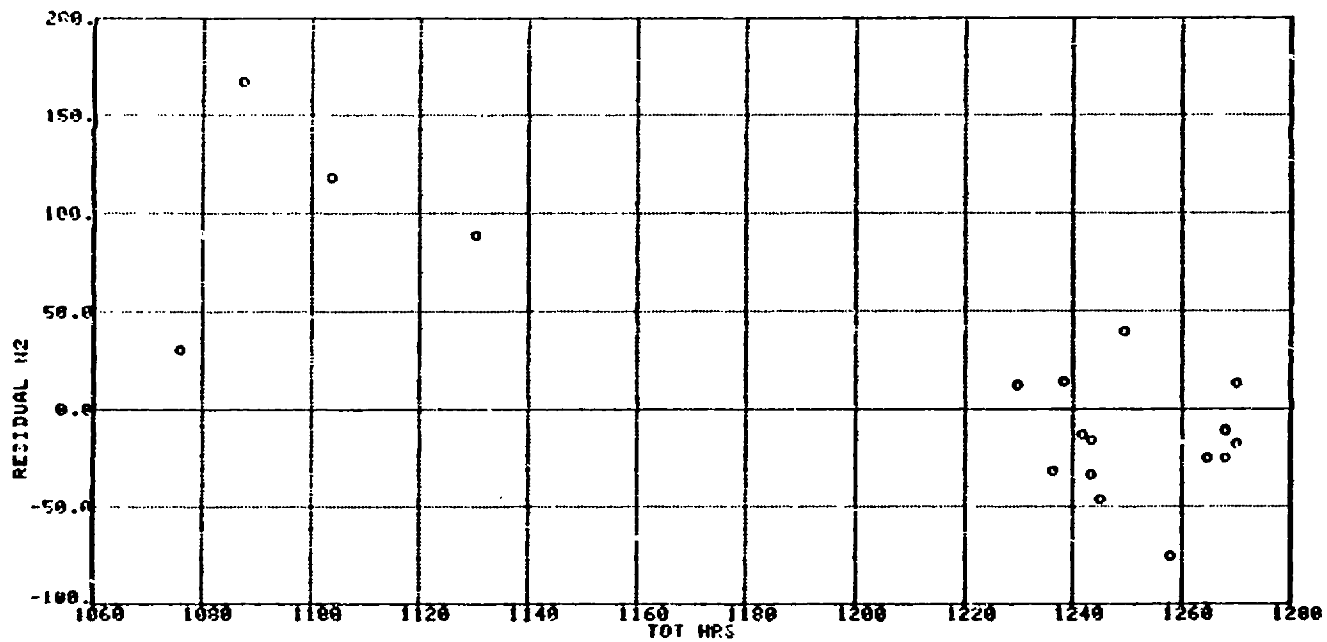

Figure 6.8 High Power EDS Data E0694: Residual N2

indication that trends are unlikely to appear in plots of the gas path parameter estimates.

Using the same methods as those applied to A10/TF34 TEMS data, EDS fault parameters were combined to form module-directed indices. The resulting module-directed rating equations are as follows:

$$\Theta_{FAN} = 0.57\Delta\eta_{FAN} - 0.82\ \Delta A_{FAN}$$

$$\Theta_{COMP} = 0.56\Delta\eta_{COMP} - 0.59\ \Delta A_{COMP} + 0.58\Delta\eta_{FC}$$

$$\Theta_{HPT} = 0.88\Delta\eta_{HT} - 0.48\ \Delta A_{HT}$$

Figures 6.9 and 6.10 are selected plots of fan, core, and net ratings as a function of operating time. Results in Figure 6.9 are not encouraging. Trends in the data are not clearly discernible. The net rating plot in figure 6.10 shows more positive results. A gradual decline in engine health over time can be seen. Because of the lack of maintenance data collected, it is not possible to demonstrate the correlation of engine health trends to maintenance actions.

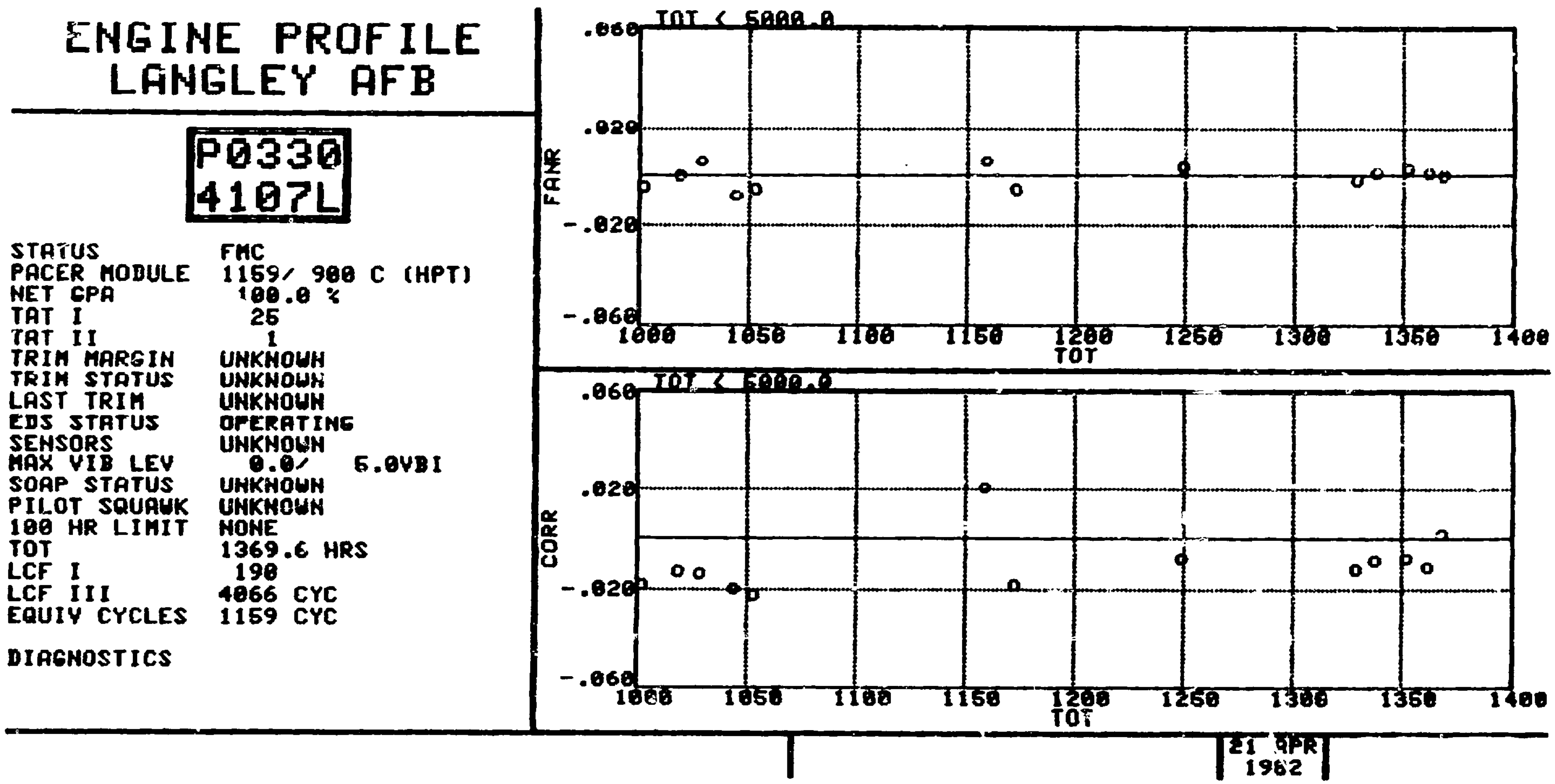

Figure 6.9 F100 Module-Directed Indices

ENGINE PROFILE
LANGLEY AFB

P0311
4108L

STATUS	FMC
PACER MODULE	1281/ 900 C (HPT)
NET GPA	100.0 %
TAT I	70
TAT II	0
TRIM MARGIN	UNKNOWN
TRIM STATUS	UNKNOWN
LAST TRIM	UNKNOWN
EDS STATUS	OPERATING
SENSORS	UNKNOWN
MAX VIB LEV	0.0/ 6.0VBI
SOAP STATUS	UNKNOWN
PILOT SQUAWK	UNKNOWN
100 HR LIMIT	NONE
TOT	1660.6 HRS
LCF I	74
LCF III	4903 CYC
EQUIV CYCLES	1281 CYC

DIAGNOSTICS

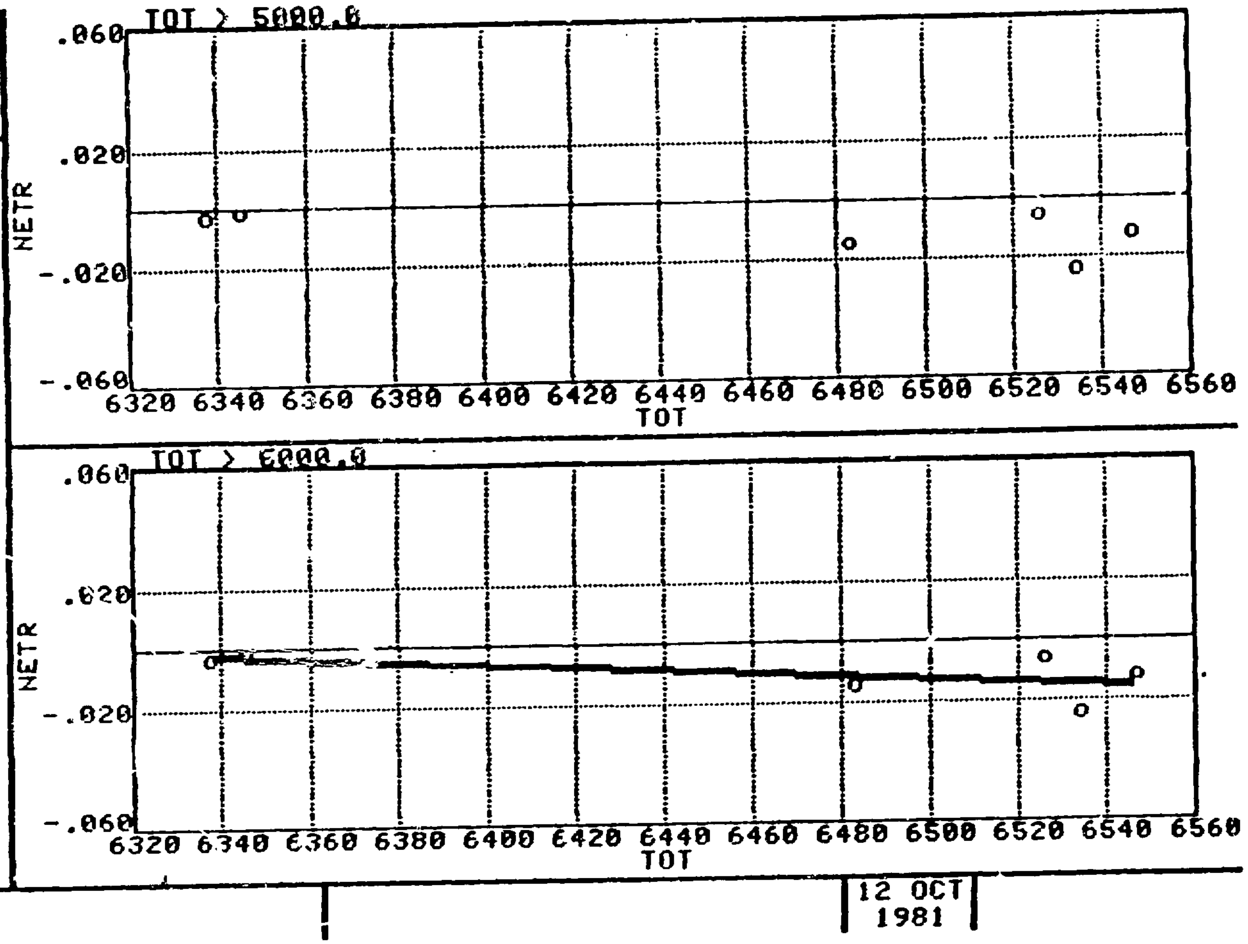

Figure 6.10 F100 Performance Rating Histories

VII. APPLICATION TO A7E/TF41 IECMS DEPLOYMENT DATA

7.1 INTRODUCTION

The following chapter presents the results of SCT's analysis of data acquired during the A7E/TF41 IECMS flight test. Test background will be briefly described and the hardware and software of the In-Flight Engine Conditioning Monitoring System (IECMS) will be characterized. Discussion of data analysis and the application of the thermodynamic cycle monitoring algorithm will proceed in four sections:

- raw data inspection
- cluster analysis with subsequent additional screening
- baseline and fault model developments
- reduction of fault parameters to module-directed indices and performance algorithm results.

7.2 TEST BACKGROUND

The data which were analyzed by SCT in the Turbine Engine Fault Detection and Isolation Program were collected by the IECMS during the flight test phase of the IECMS Program. The A7E IECMS was deployed aboard the U.S.S. KENNEDY for the four-month period from 8/80 through 12/80. Data were collected for 35 engines which included:

- 40,000 frames of IECMS collected data consisting of functional check flight data and brief history data (take-off, lift-off, and trend)
- a maintenance action file containing 200 maintenance actions issued via VIDS/MAF forms

7.3 IECMS DESCRIPTION

The A7E/TF41 IECMS is a system which was designed for the U.S. Navy attack aircraft. The program was initiated in 1969 with work done jointly by

Vought Aircraft and Detroit Diesel Allison to develop an automated integrated data system.

The system is comprised of four major subsystems. These are:

- engine kit
- avionics kit
- airframe change kit
- data processing station

The engine kit contains transducers, switches, electrical harnesses, and plumbing necessary to monitor 40 engine parameters. The avionics kit consists of the engine analyzer unit, flag display unit, and tape magazine unit. These components monitor and signal condition engine parameters, activate cockpit lights, provide exceedance information and record data as required. The airframe change kit includes the cockpit panel, caution advisory panel, IECMS compartment and wiring harness/sensors. This hardware provides for the interface of the IECMS with the airframe and engine, and houses the IECMS self-test advisory signals. The data processing station is ground-based and consists of a minicomputer, tape drive, and interface units, a line printer, and a teletype. The station processes the in-flight data, outputs diagnostic advisories, and stores the data on a magnetic tape for further processing at the central computer facility.

The IECMS hardware continuously monitors engine parameters, while the software determines operational modes and the need for recording data. Data are collected during the following operational conditions [48,49]:

- engine exceedance
- marked rate of change in NH, PLA, or T5
- normal recording mode (single frame recording - 5.6 seconds of data)
  - start
  - ground idle
  - take-off
  - vibration
  - cruise
  - end of flight

Diagnostic indicators on the flag display unit provide a go/no-go message. Data which are collected on the airframe can be transferred to the ground-based data processing station via tape transcription. Ground-based processing yields diagnostic summaries for each flight, documentary data and diagnostic information related to the flight.

7.4 DATA INSPECTION

Before analyzing the data, plots of raw data were made for several engines for the purpose of visual inspection. The plots reveal the character of the data and bring to light some anomalies which must be borne in mind when evaluating the application of the thermodynamic cycle monitoring algorithm to the data.

The unstable character of the IECMS take-off data frames indicated that these data would not be suitable for processing by the thermodynamic cycle monitoring algorithm. This relatively small amount of data was therefore not included in the subsequent processing. Upon transfer to the MIMS, vibration data were labelled as mode 2000 for identification purposes. Since these data are typically recorded within a few hundred feet after take-off, the IECMS vibration data will hereafter be referred to as take-off data or mode 2000 data. Cruise data were labelled as mode 4000 data.

Figures7.1 through 7.3 show Julian date plotted as a function of total operating time. They reveal that for the engines shown, one of the two variables or both were incorrectly recorded. Because the thermodynamic cycle monitoring algorithm is designed to predict engine health as a function of operating time, its successful application to these data is hindered. These inconsistencies also make it impossible to arrive at meaningful conclusions when correlating engine health trends with maintenance action data.

7.5 CLUSTER ANALYSIS AND DATA SCREENING

As described in Section 7.3, IECMS data are normally recorded during six predefined modes of engine operation. Data are collectively written to a single file where the data types are identified in the respective data

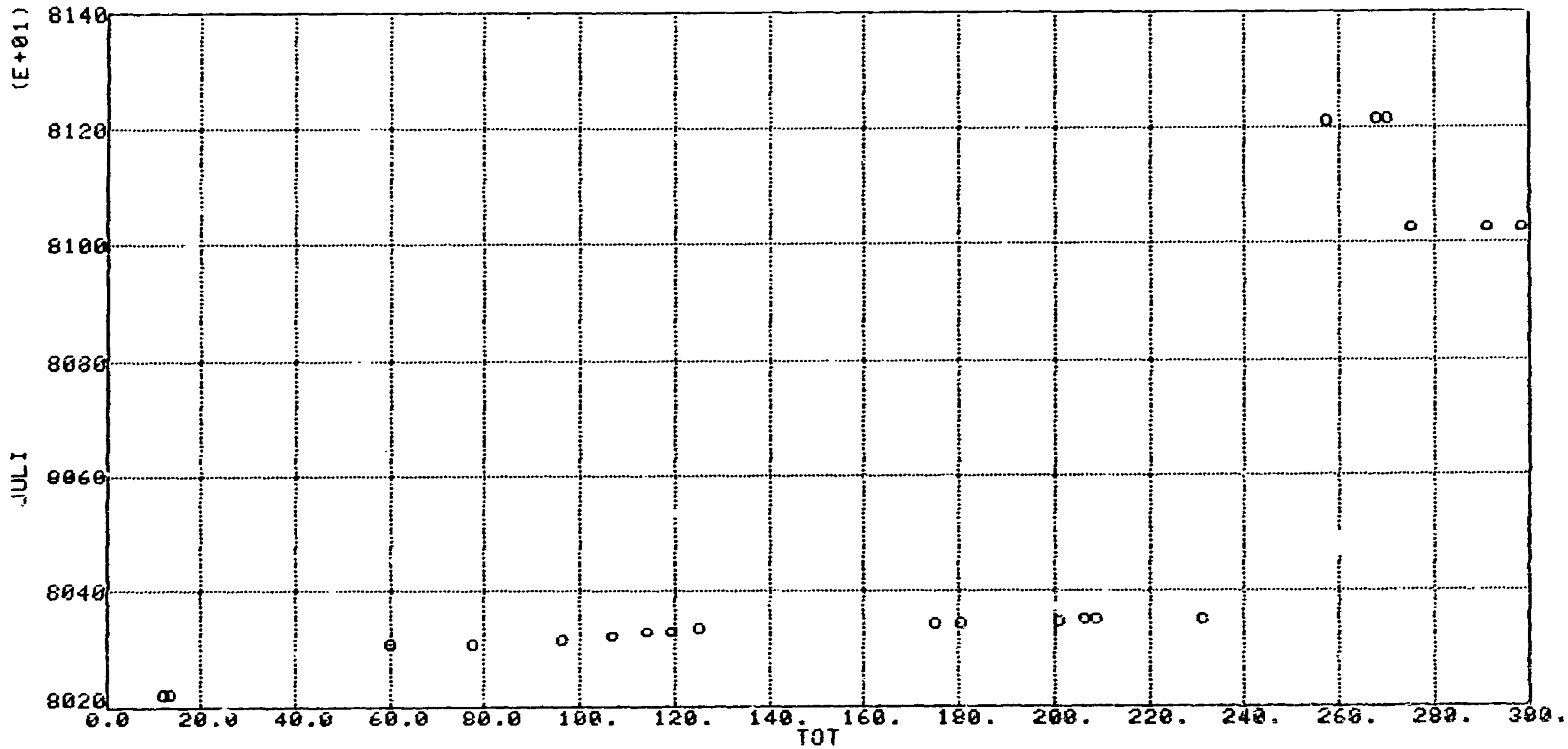

Figure 7.1 E1614 Takeoff Data: Juli vs. TOT (140 Pts.)

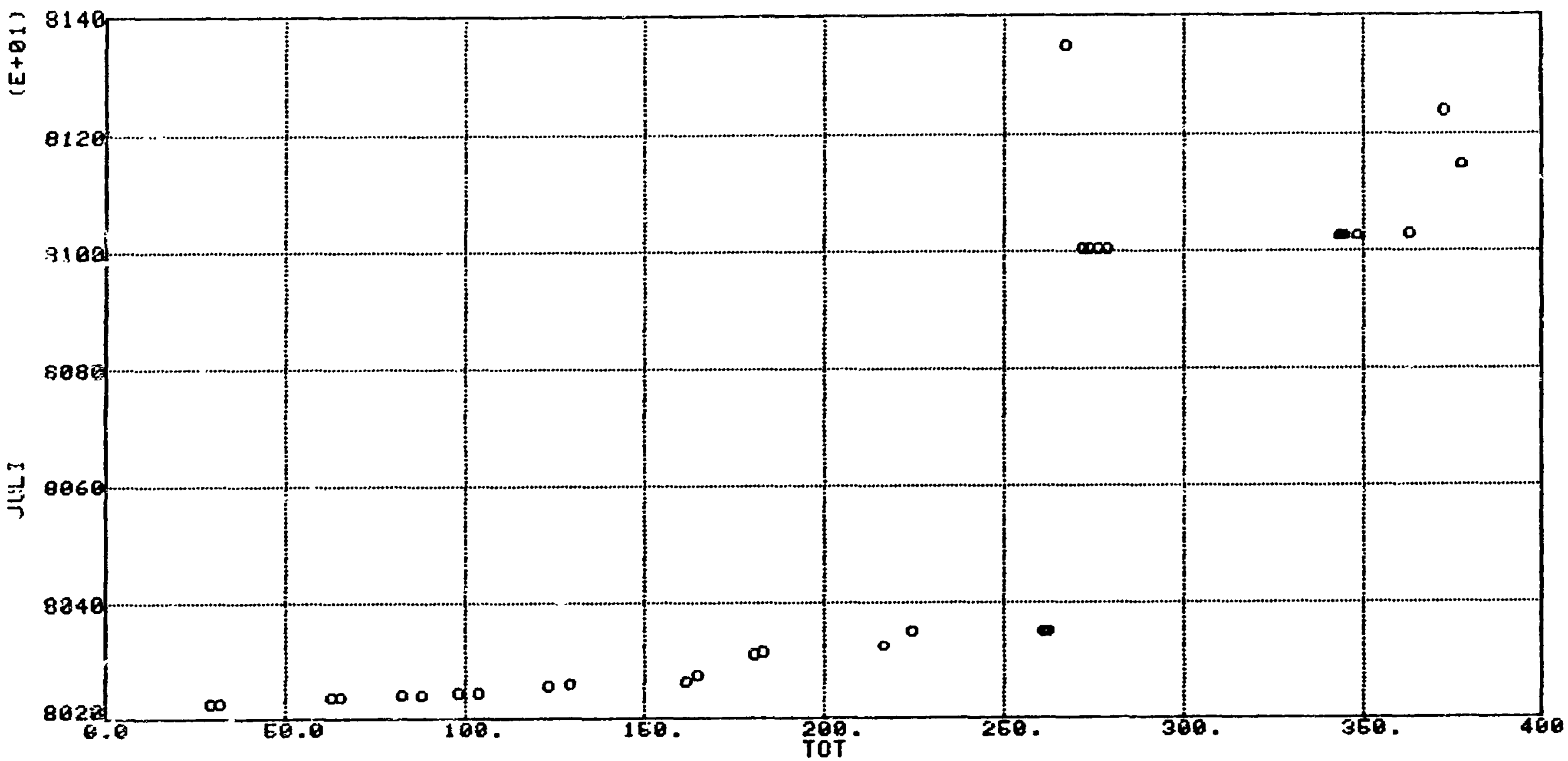

Figure 7.2 E2553 Takeoff Data: Juli vs. TOT (156 Pts.)

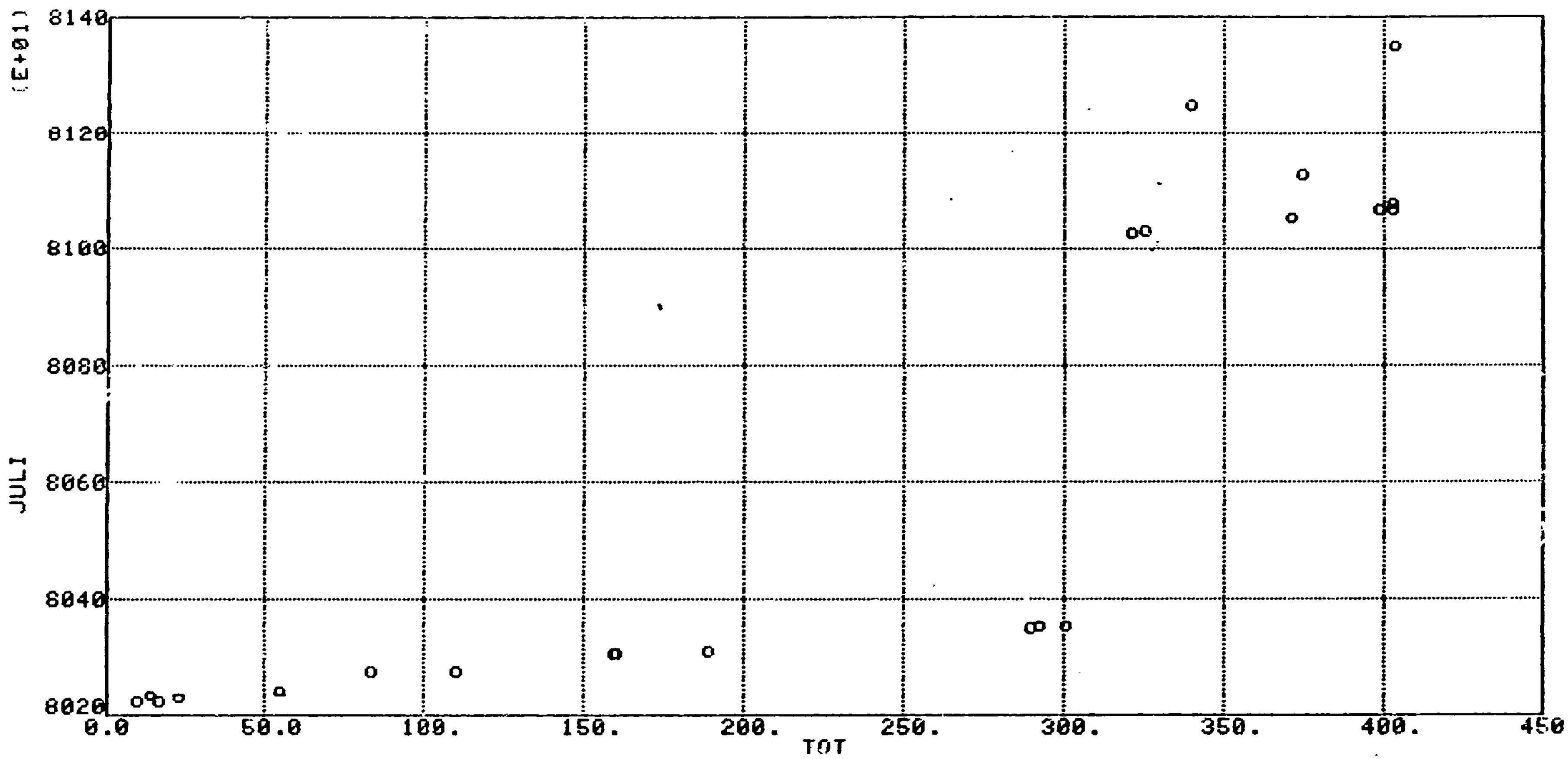

Figure 7.3 E1243 Takeoff Data: Juli vs. TOT (80 Pts.)

records. Data were sorted according to recording mo[illegible] and three subsets of data were created; cruise data, take-off data, and a combined set of data. Grouping of data in this fashion allows for a more uniform distribution of points, making it amenable to input to the thermodynamic cycle monitoring algorithm.

The cluster analysis program which was described in Chapter VI was executed on these data sets and used to define data screening limits. For each data set, maximum and minimum values were found for each of 17 channels. These values are listed in Table 7.1. Additionally, the data were plotted to allow for visual inspection of the data distribution. Figures 7.4 through 7.6 illustrate the clustering of data according to operational mode. With this information, suitable margins were added/subtracted from the maximum and minimum values. Table 7.2 lists the screening limits which were finally applied to the cruise and take-off data sets. Of the 1988 points originally in the take-off data set, and the 2149 points in the cruise data set, 1660 and 1537 points remained in each of these sets, respectively, subsequent to screening. This screening process eliminates data scans with hard sensor failures. Only 20 percent of the frames are rejected by this process, indicating that deficiencies in the data due to hard sensor failures were minor.

7.6 BASELINE AND FAULT MODEL DEVELOPMENT

Baseline engine models were created for each of the two data sets for 12 variables. Table 7.3 provides a statistical summary of the model accuracies. The smaller standard deviations seen in the take-off data support the conclusions presented in Chapter VI that take-off mode data are more repeatable the cruise mode data.

Residual plots of engine variables which were made during baseline model development provide an indication of the applicability of the thermodynamic cycle monitoring algorithm to IECMS data. Figures 7.7 through 7.9 illustrate the dynamic characteristics of the data. IECMS data were grouped into 5-hour windows for trending purposes. The resulting data consisted of roughtly 1 to 11 trend points per engine over 200 hours of total operating time. Plots of

Table 7.1
Maximum and Minimum Values of Data Sets

CRUISE MODE DATA

	NUMBER OF POINTS		2149
	CHANNEL	MINIMUM	MAXIMUM
1	FHMG	-130.13	130.00
2	PS3	- 79.485	376.60
3	T3	-482.72	839.55
4	T5	-627.20	584.41
5	PT51	-0.58651	50.000
6	WF	0.00000E+00	34130.
7	NH	7.4715	1510.2
8	NL	7.3814	138.25
9	ALT	-1000.0	0.24718E+06
10	MACH	0.00000E+00	9.8958
11	PLA	-6.0044	335.67
12	OAT	-56.406	96.909
13	T1	-76.904	75.640
14	IGV	-109.74	139.68
15	TOT	0.69008	1077.5
16	MODE	4000.0	4000.0
17	JULI	80013.	81354

Table 7.1 (Continued)

TAKE-OFF MODE DATA

NUMBER OF POINTS	CHANNEL	MINIMUM	1988 MAXIMUM
1	PHMG	-130.13	130.00
2	PS3	-218.12	294.77
3	T3	-341.54	738.15
4	T5	-464.78	623.47
5	PT51	12.317	50.000
6	WF	54.056	28363.
7	NH	25.297	3022.7
8	NL	26.353	421.78
9	ALT	-1000.0	0.24712E+06
10	MACH	0.53768E-01	2.5002
11	PLA	-1.1270	350.08
12	OAT	-56.213	148.27
13	T1	8.2004	48.131
14	IGV	-117.80	121.24
15	TOT	0.29507E-01	1077.2
16	MODE	2000.0	2000.0
17	JULI	80013.	81354.

Table 7.1 (Continued)

CRUISE AND TAKE-OFF MODE DATA

	NUMBER OF POINTS		4137
	CHANNEL	MINIMUM	MAXIMUM
1	PHMG	-130.13	130.00
2	PS3	-218.12	376.60
3	T3	-482.72	839.55
4	T5	-627.20	623.47
5	PT51	-0.58651	50.000
6	WF	0.00000E+00	34130.
7	NH	7.4715	3022.7
8	NL	7.3824	421.78
9	ALT	-1000.00	0.24718E+06
10	MACH	0.00000E+00	9.8958
11	PLA	-6.0044	350.08
12	OAT	-56.406	148.27
13	T1	-76.904	75.640
14	IGU	-117.80	139.68
15	TOT	0.29507E-01	1077.5
16	MODE	2000.0	4000.0
17	JULI	80013.	81354.

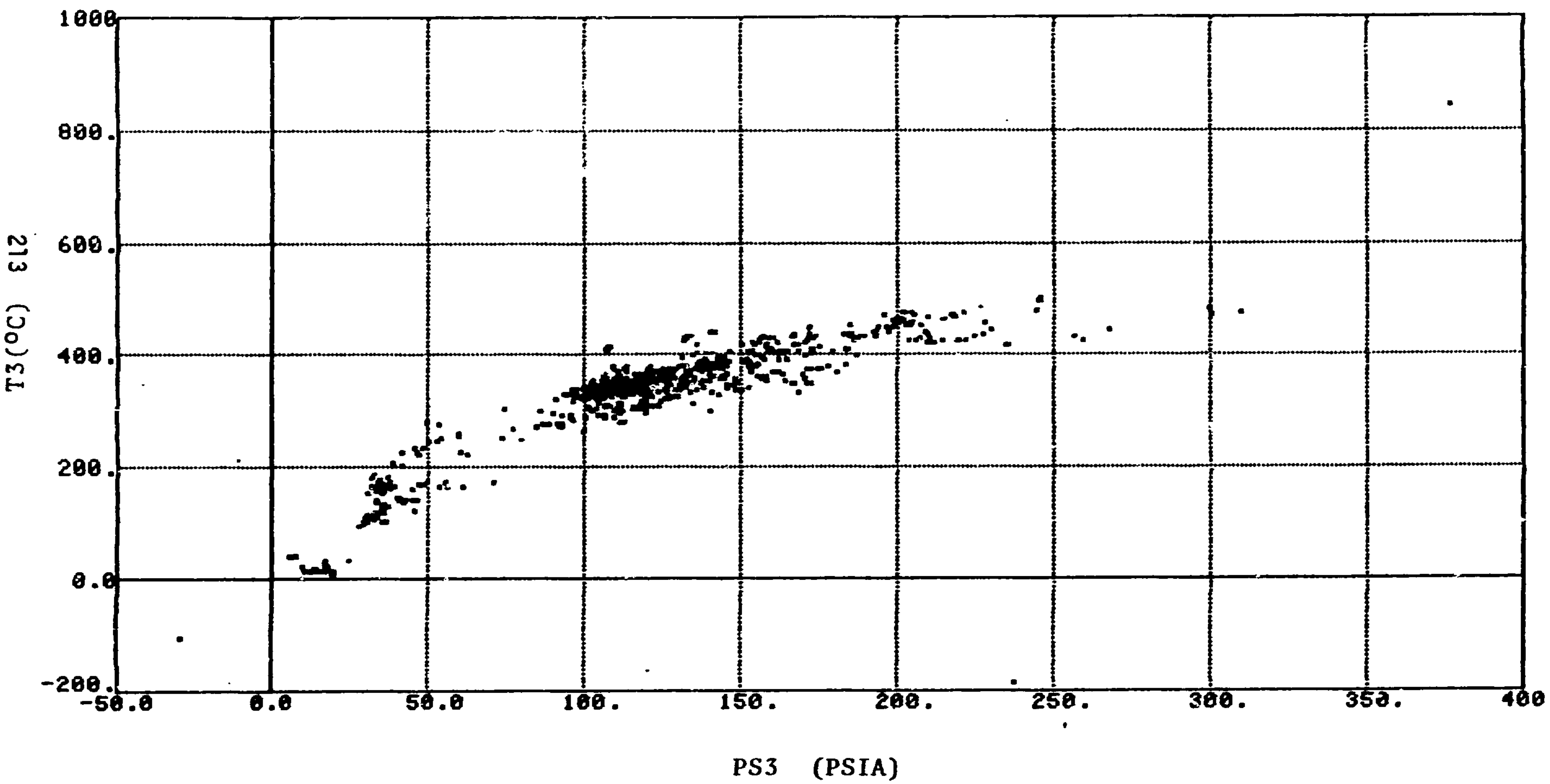

Figure 7.4 Takeoff Data Distribution Plot

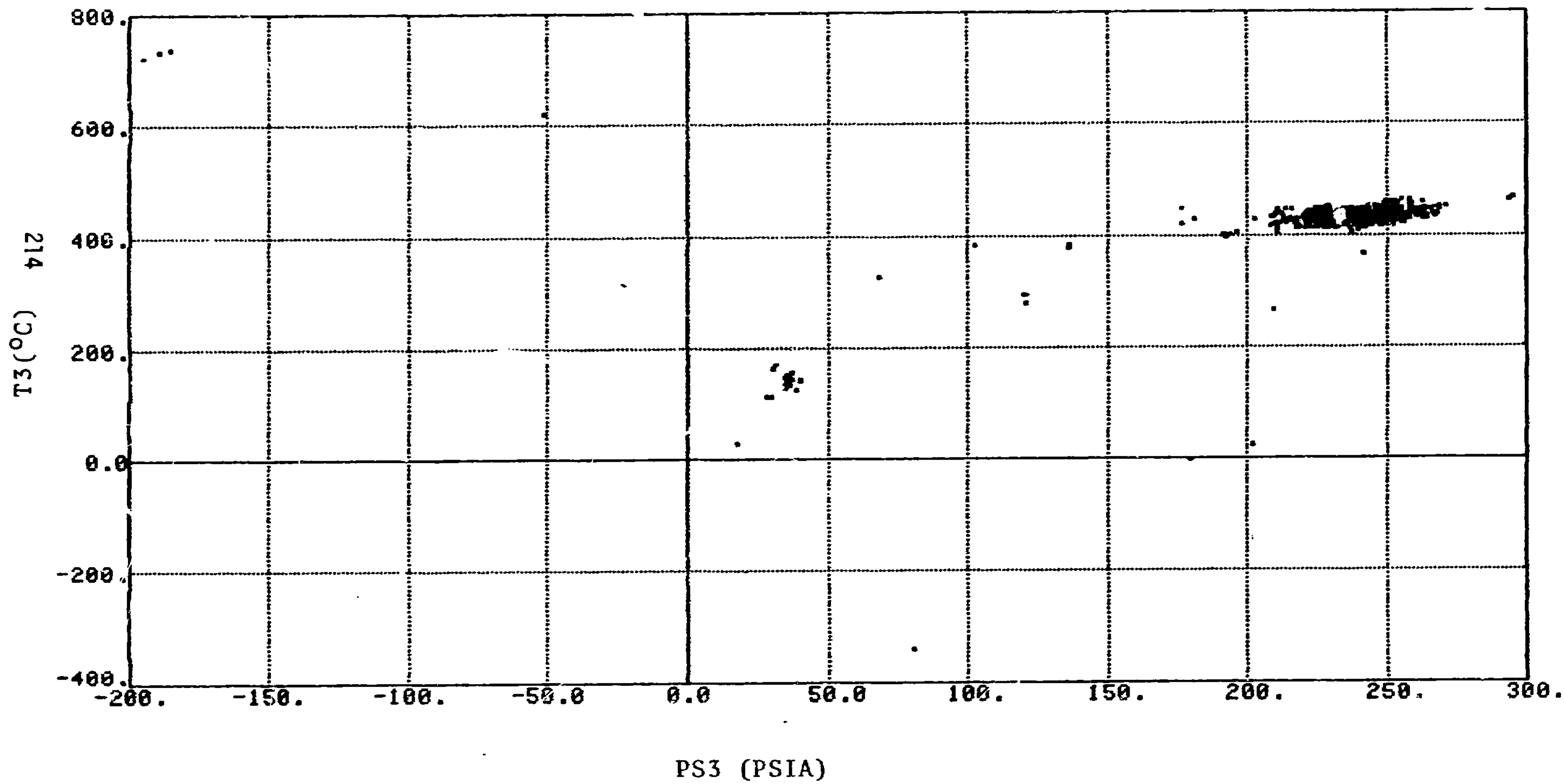

Figure 7.5 Cruise Data Distribution Plot

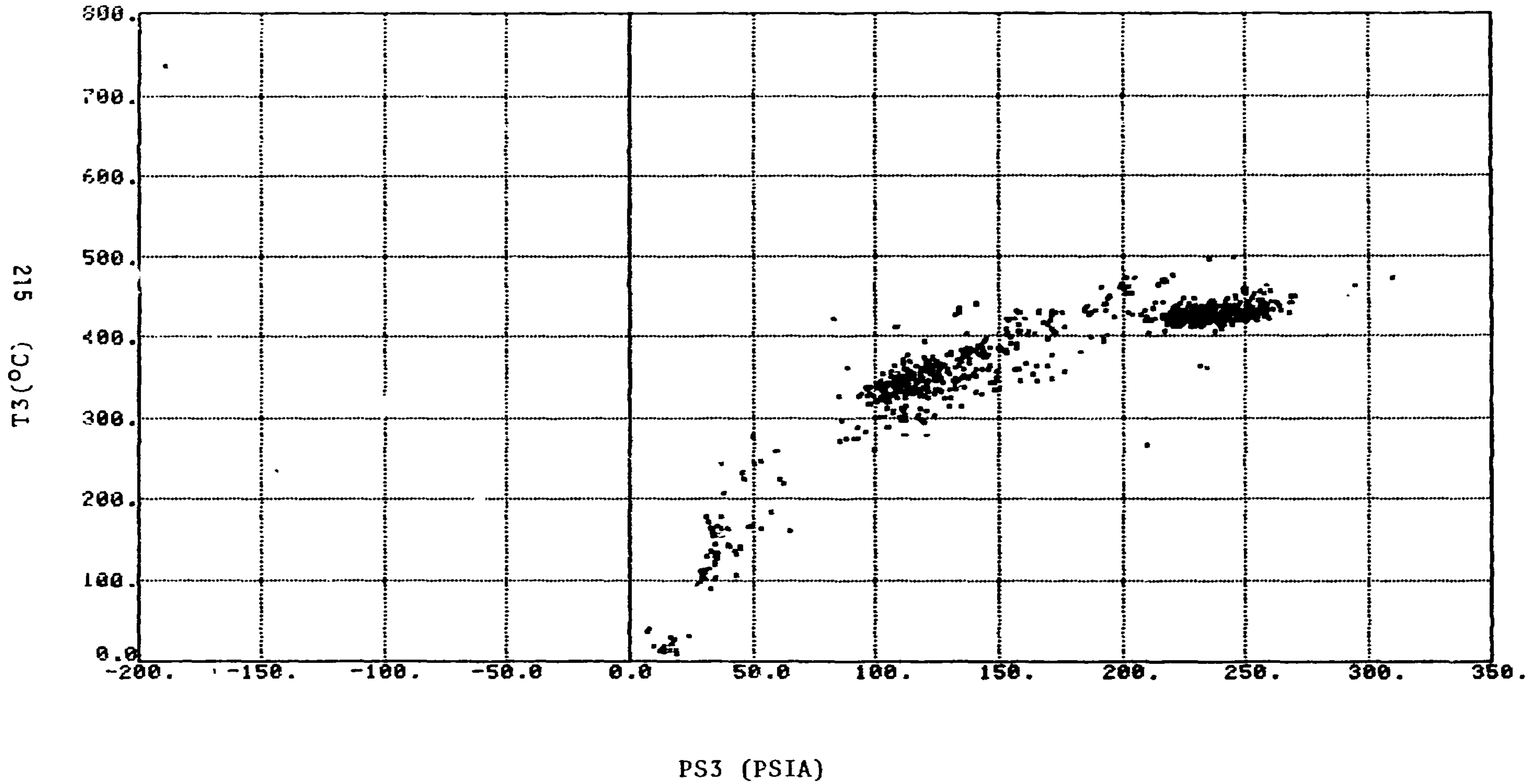

Figure 7.6 Combined Data Set Distribution Plot

Table 7.2
IECMS Data Screening Limits

		TAKE-OFF MODE		CRUISE MODE	
		LOW	HIGH	LOW	HIGH
1	PS3	200	280	100	250
2	T3	350	500	350	500
3	T5	500	650	500	600
4	PT51	25	45	10	40
5	WF	5,000	13,000	5,000	10,000
6	NL	80	100	80	100
7	NH	80	100	80	110
8	ALT	-1000	50,000	-1000	50,000
9	MACH	.01	.95	.01	.95
10	PLA	5	95	5	95
11	OAT	-25	140	-25	140
12	T1	-10	100	-10	100

Table 7.3
IECMS Baseline Model Statistical Summaries

	TAKE-OFF DATA				CRUISE DATA		
CHAN	VAR	S	R^2	σ	S	R^2	σ
1	PS3	12.00	61.3	7.46	40.5	92.5	11.1
2	T3	9.01	68.8	5.03	72.0	98.3	9.27
3	T5	6.02	25.1	5.21	54.8	88.3	18.7
4	PT51	1.74	50.1	1.23	4.56	71.5	2.43
5	WF	818	54.5	552	1410	93.2	369
6	NL	1.25	84.3	.496	14.4	96.5	2.68
7	NH	.709	54.8	.476	8.34	98.2	1.12
8	ALT	589	6.71	569	6310	82.7	2630
9	MACH	.0282	7.91	.0270	.154	71.6	.0821
10	PLA	5.95	10.1	5.64	10.7	79.0	4.90
11	OAT	16.2	19.0	14.6	13.7	63.9	8.25
12	T1	8.05	68.5	4.52	12.7	62.6	7.74

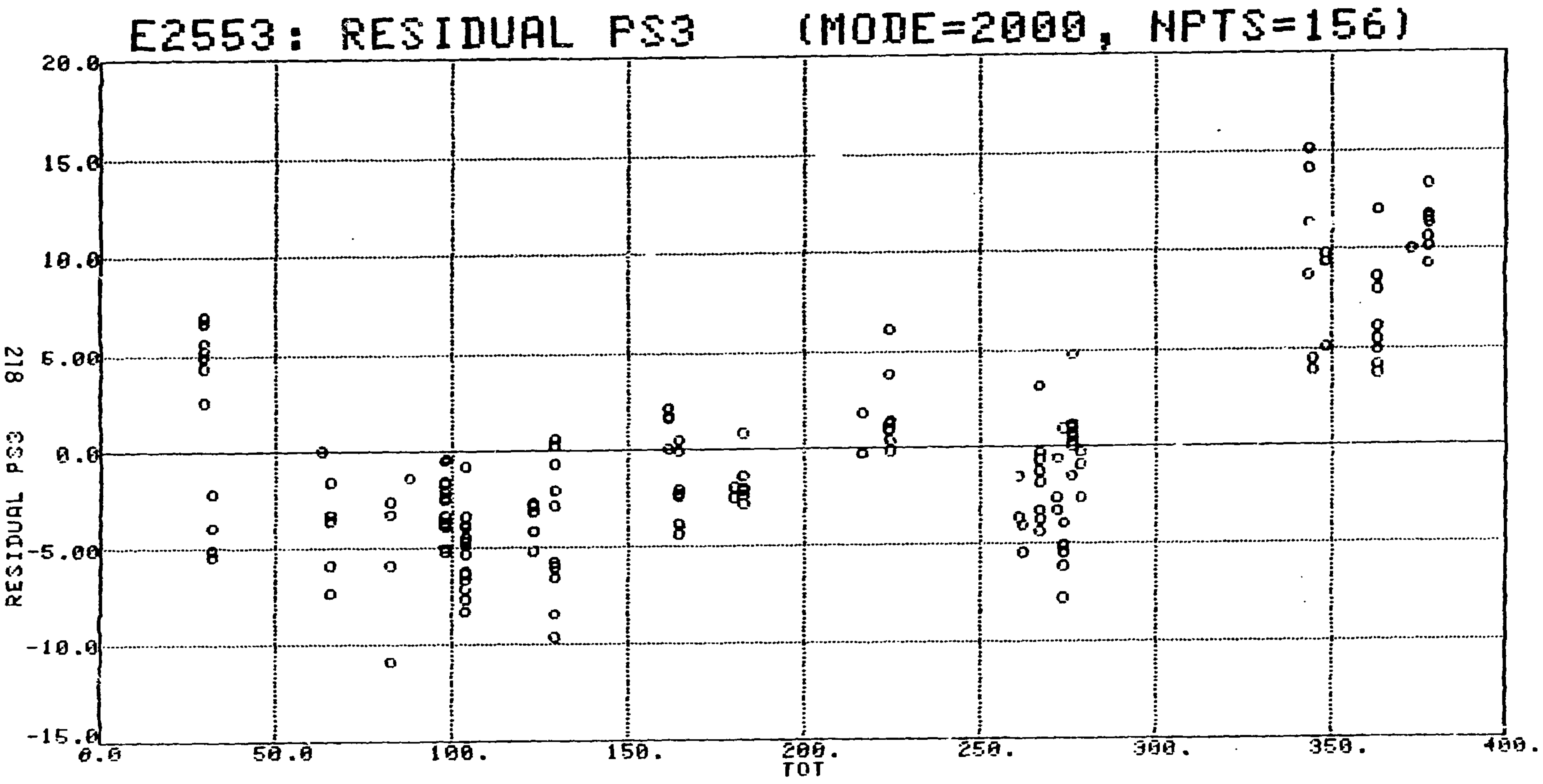

Figure 7.7 IECMS Takeoff Data

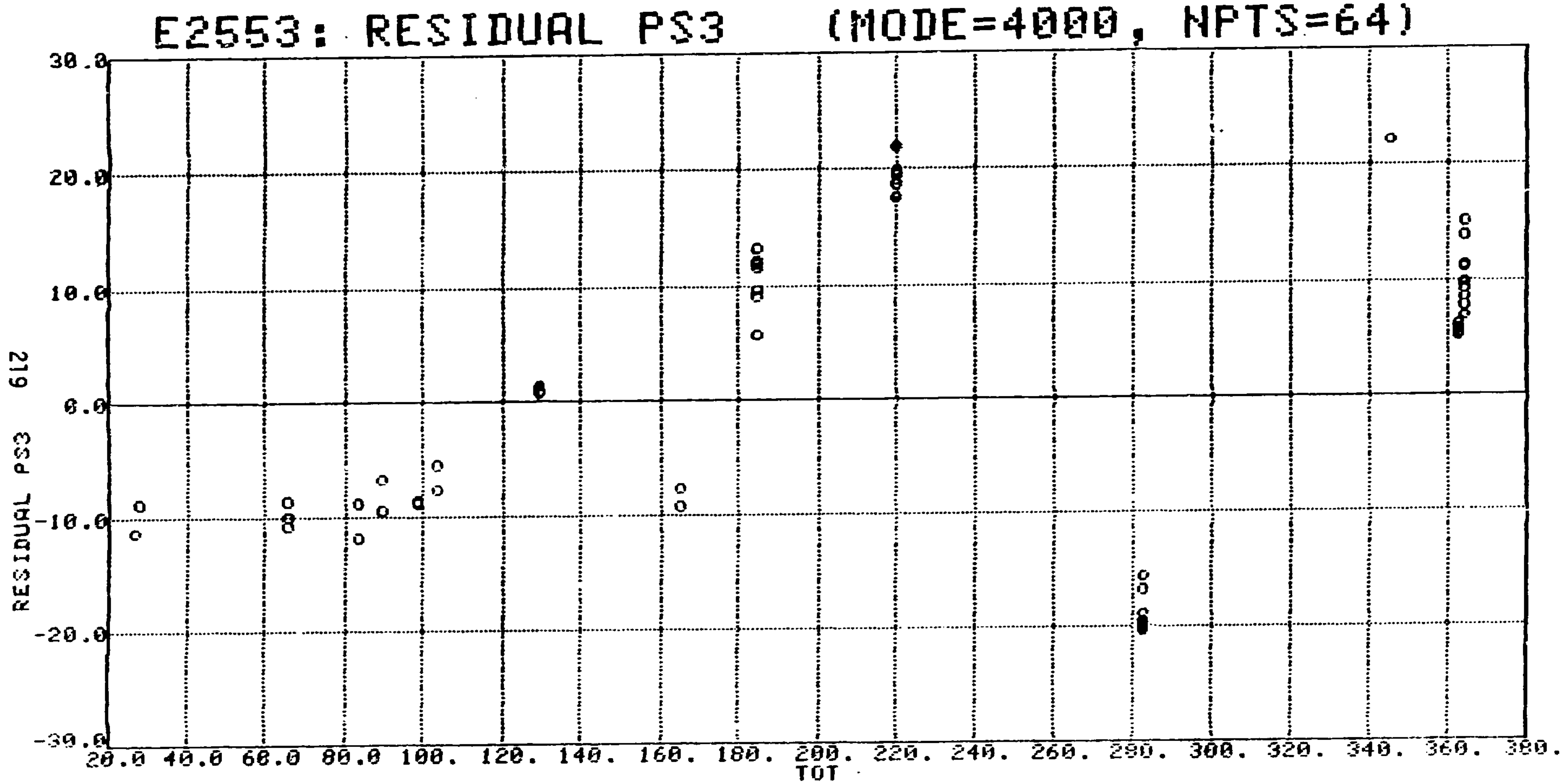

Figure 7.8 IECMS Cruise Data (E2553)

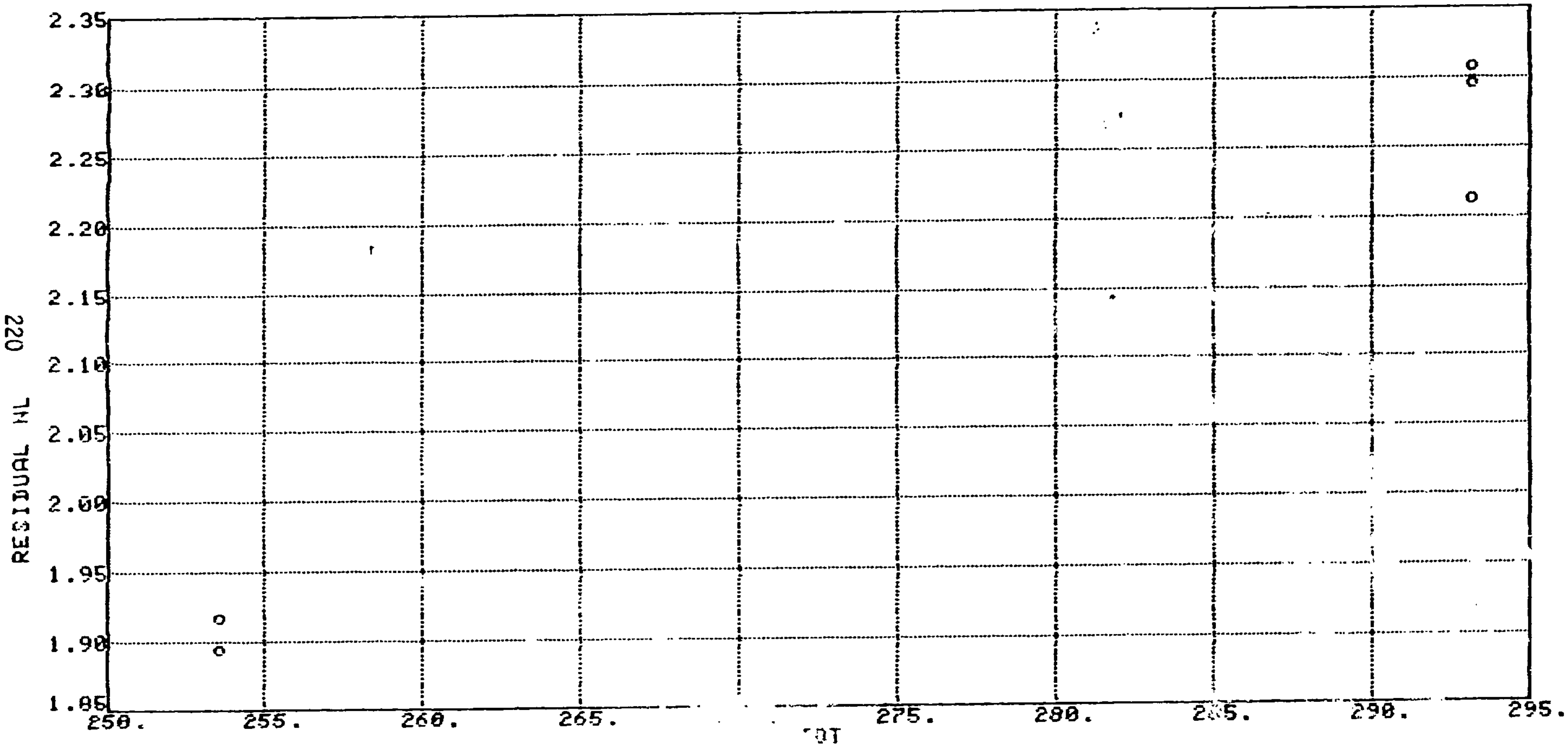

Figure 7.9 IECMS Cruise Data (E1226)

these data show large gaps in the data which impede trending. What appeared initially to be a voluminous set of data actually amounts to a smaller set of data (on a per-engine basis) collected at irregular intervals (see Figure 7.9). Experience with TEMS and EDS data showed that for trending purposes, it would be more desirable to have one to two repeatable data points per flight (per engine).

The residual plots also give an indication of the accuracy of the baseline model. Points plotted in Figures 7.7 and 7.8 show that the points are scattered around zero, an indication of the correctness of the models. The plots also provide further evidence that take-off data is more repeatable than cruise data. Figures 7.7 and 7.8 show that the residual PS3 for engine 2553 is more closely scattered about zero for take-off mode data than for cruise mode data.

Using a procedure similar to that used in developing baseline models, fault models were extracted from TF41 status deck data. The data base used for this purpose was created by executing the status deck over a range of flight conditions. For each set of flight conditions, the program was executed while varying engine component efficiencies and flow areas (i.e. fault parameters). Table 7.4 lists the flight conditions chosen for this purpose. The values were chosen to be compatible with the flight conditions of the in-flight engine data, and consistent with variations in efficiencies and areas which characterize the engine design. A list which defines the efficiencies and areas and the percent deviations of these variables is provided in Table 7.5.

7.7 MODULE-DIRECTED RATING PARAMETERS/PERFORMANCE ALGORITHM RESULTS

By taking linear combinations of engine fault parameters, three module-directed indices were created for the IECMS. The ratings correspond to the low-spool, high-pass turbine and compressor sections of the engine. A net rating corresponds to the average of these three parameters. Trend plots of the ratings as a function of time are subject to interpretation. There are, however, a few conclusions which can be made with some degree of certainty.

Table 7.4

Flight Conditions for Fault Model Data Base

ALT (FT)	MN	NH (RPM)
0.	0.	9,750
5,000	.2	10,400
7,500	.4	11,050
		11,700
		12,350

Table 7.5
Fault Parameter Definitions and Perturbations

$\Delta\eta_C$	CORE EFFICIENCY DELTA	.97, .99, 1.0, 1.01, 1.03
$\Delta\eta_F$	FAN EFFICIENCY DELTA	
$\Delta\eta_{HT}$	HIGH PASS TURBINE EFFICIENCY DELTA	
$\Delta\eta_{LT}$	LOW PASS TURBINE EFFICIENCY DELTA	
ΔA_C	CORE AREA DELTA	.95, .97, 1.0, 1.03, 1.05
ΔA_F	FAN AREA DELTA	
ΔA_{HT}	HIGH PASS TURBINE	
ΔA_{LT}	LOW PASS TURBINE AREA DELTA	

Sample results are presented in Figures 7.10 through 7.15. A plot of residual T3 for engine 2553 (Figure 7.10) shows a marked jump at 125 operating hours. This jump is correlated with a jump in engine vibration in Figure 7.11. It is conceivable that increased vibration affected the T3 sensor to produce the jump in the temperature readings.

Figures 7.12 and 7.13 show the low-spool rating (θ_1) and compressor rating (θ_2) for engine 1930 plotted as a function of engine operating time. These plots show declining ratings over time with jumps which may correspond to engine maintenance actions. However, the lack of maintenance data together with gaps in the data prevent firm conclusions from being drawn.

Also shown in Figures 7.12 and 7.13 are the uncertainty bands around each parameter estimate. These bands indicate the degree of confidence in each parameter estimate. One factor in determining these bands are the number of original data points in the 5-hour window. The large uncertainty in the estimate of θ_1 at 120 hours (Figure 7.13) is caused by having only two data points in the window (see Figure 7.14). As the number of points within each window increases, the uncertainty in the parameter estimates decreases.

Figure 7.15 shows a low-spool parameter plot for engine 2553. Here also, short-term declines in the parameter are shown. Improvements in the module health rating at 170 hours and 300 hours may be due to maintenance actions. The gap in the data between 280 and 340 hours prevents the exact time of the jump from being determined.

Most of the plots lend evidence supporting the conclusion that take-off data are more amenable to trending algorithms than cruise data. An illustration of this is shown in Figures 7.16 through 7.19, where health parameters and corresponding confidence intervals are plotted for engines 1333 and 1243. These plots show that the confidence intervals are much smaller for the take-off data. The question remains to be determined, however, whether this increased certainty in the parameter estimates is due to the number of data points used in calculating the estimate, or to the correlation of parameter residuals.

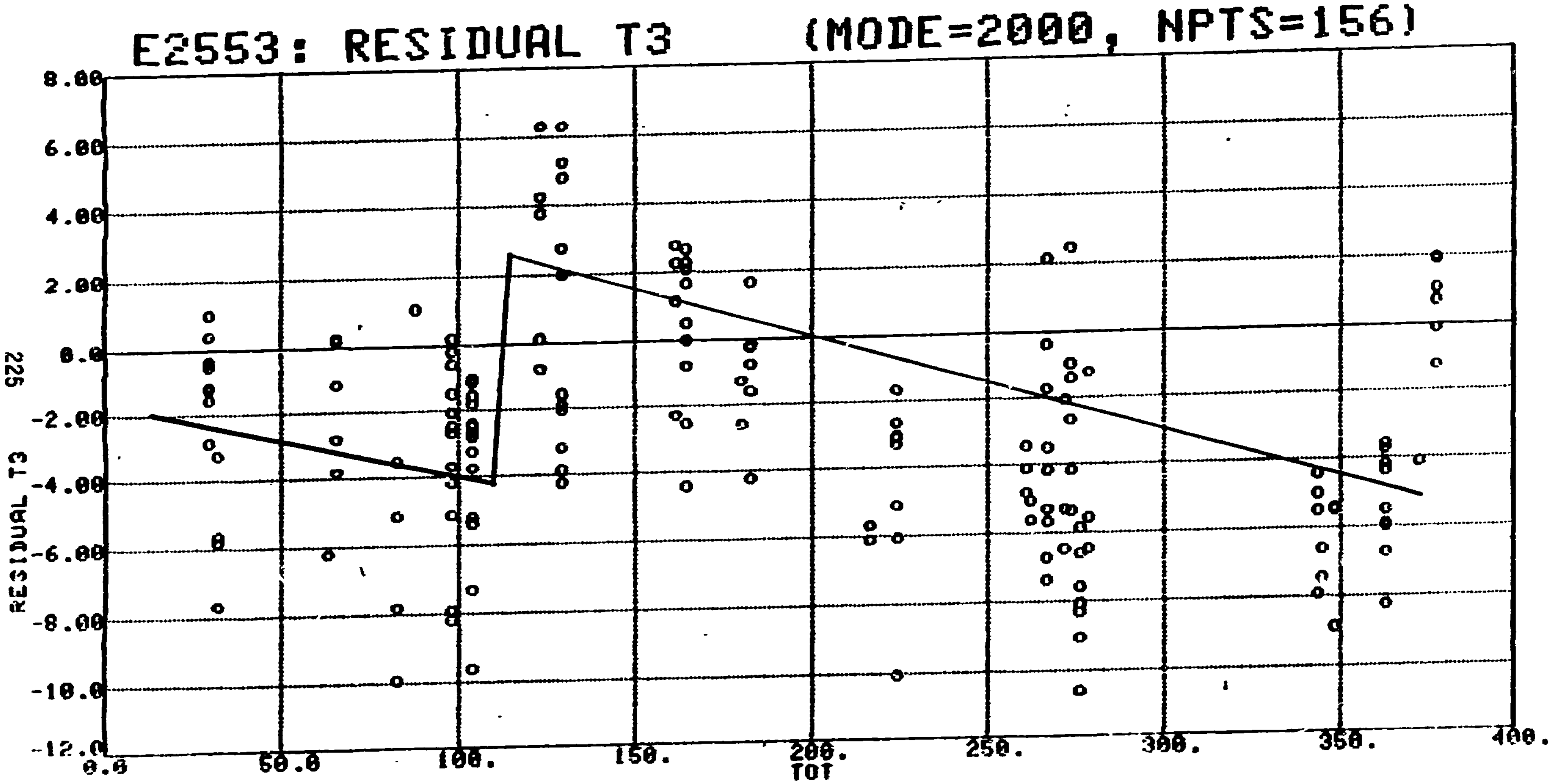

Figure 7.10 E2553: Residual T3

ENGINE PROFILE
USS KENNEDY

2553
0401L

STATUS	FMC
PACER ITEM	290.0/2500.0C (HPC)
NET CPA	100.0 %
TSC	8654.5
NHCY	290.0
NLCY	396.0
IECMS STATUS	OPERATING
SENSORS	UNKNOWN
MAX VIB LEV	0.9/ 0.0VAO
PILOT SQUAWK	
100 HR LIMIT	NONE
TOT	377.4HRS

DIAGNOSTICS

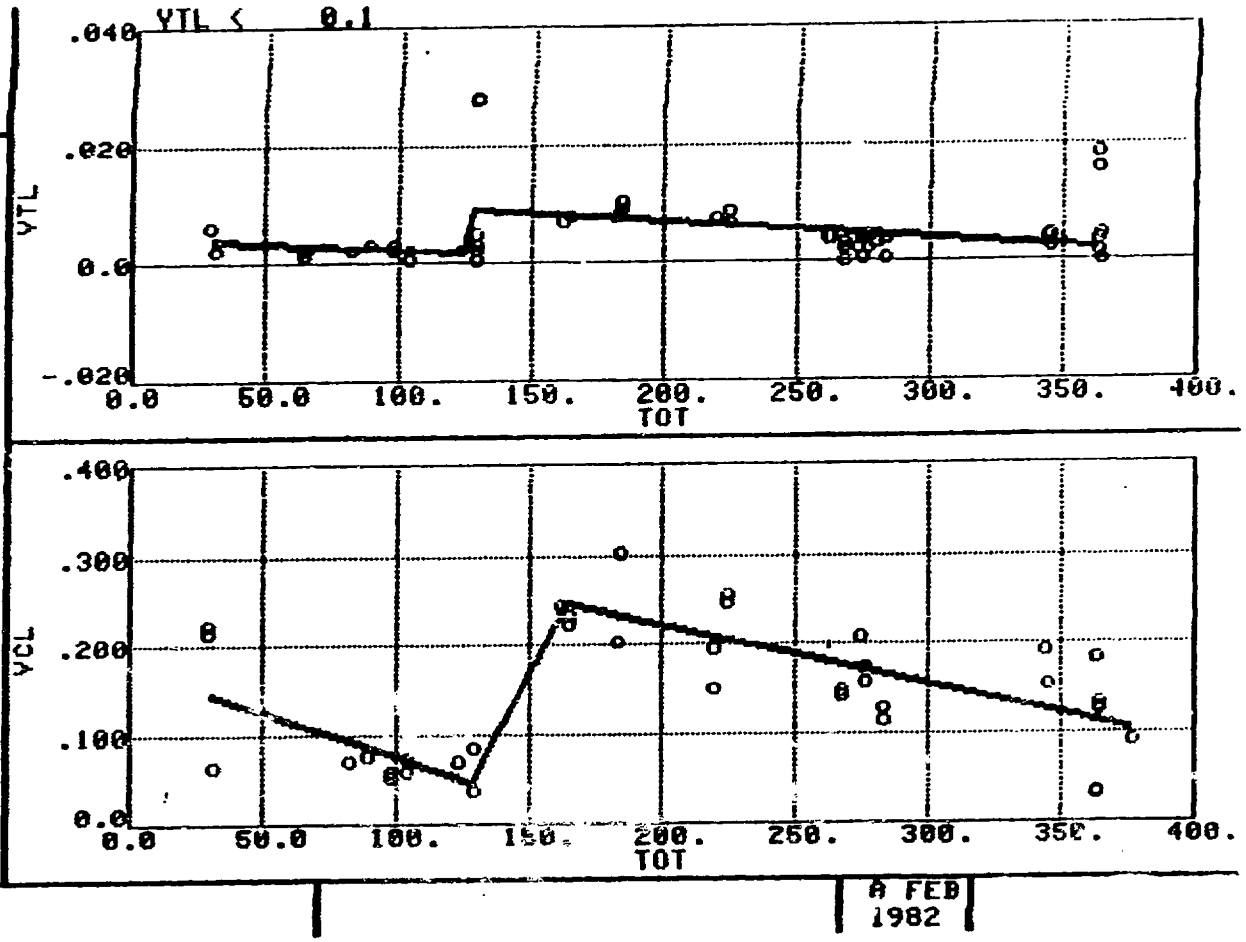

Figure 7.11 Vibration History for E2553

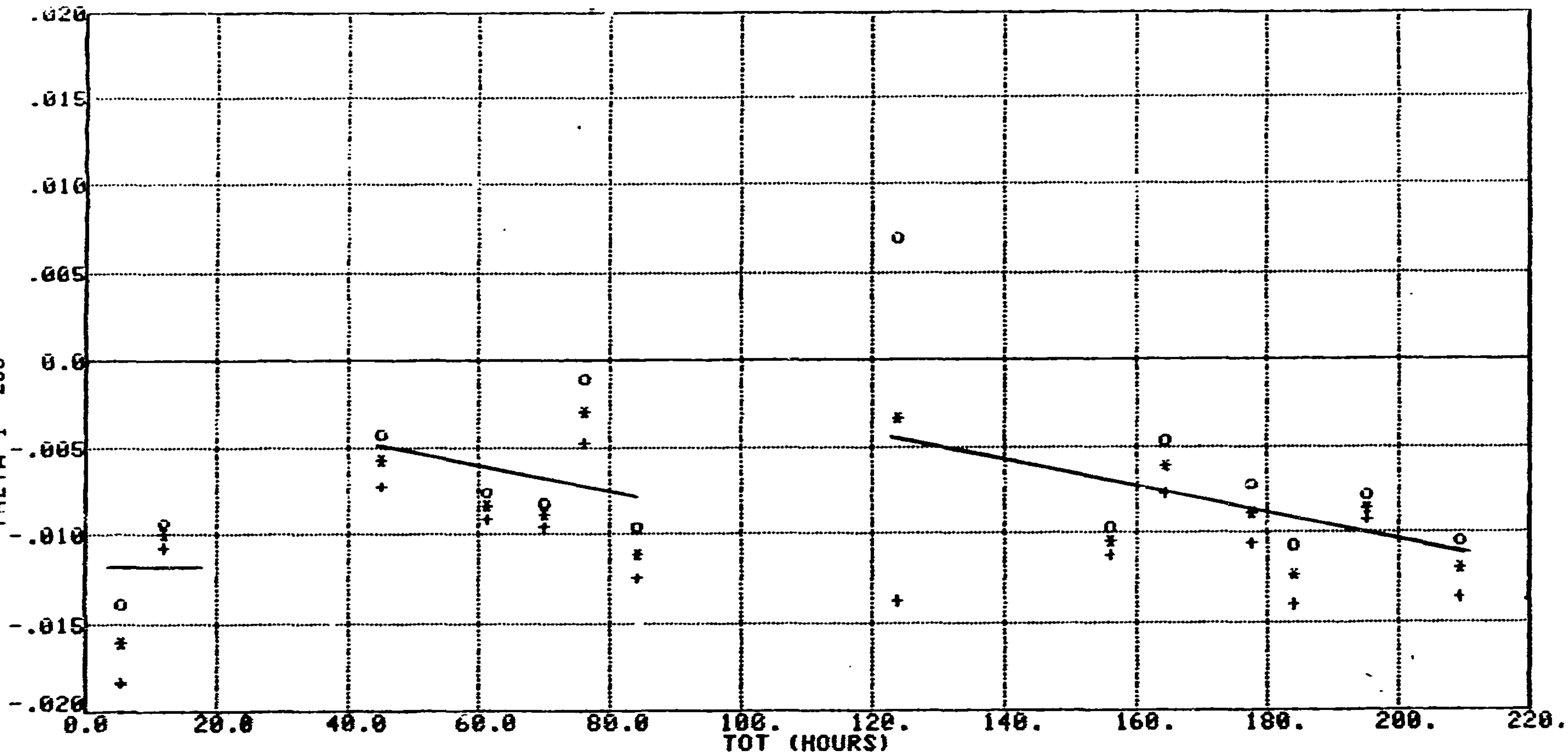

Figure 7.12 Low Spool Rating For E1930 (Mode 2000)

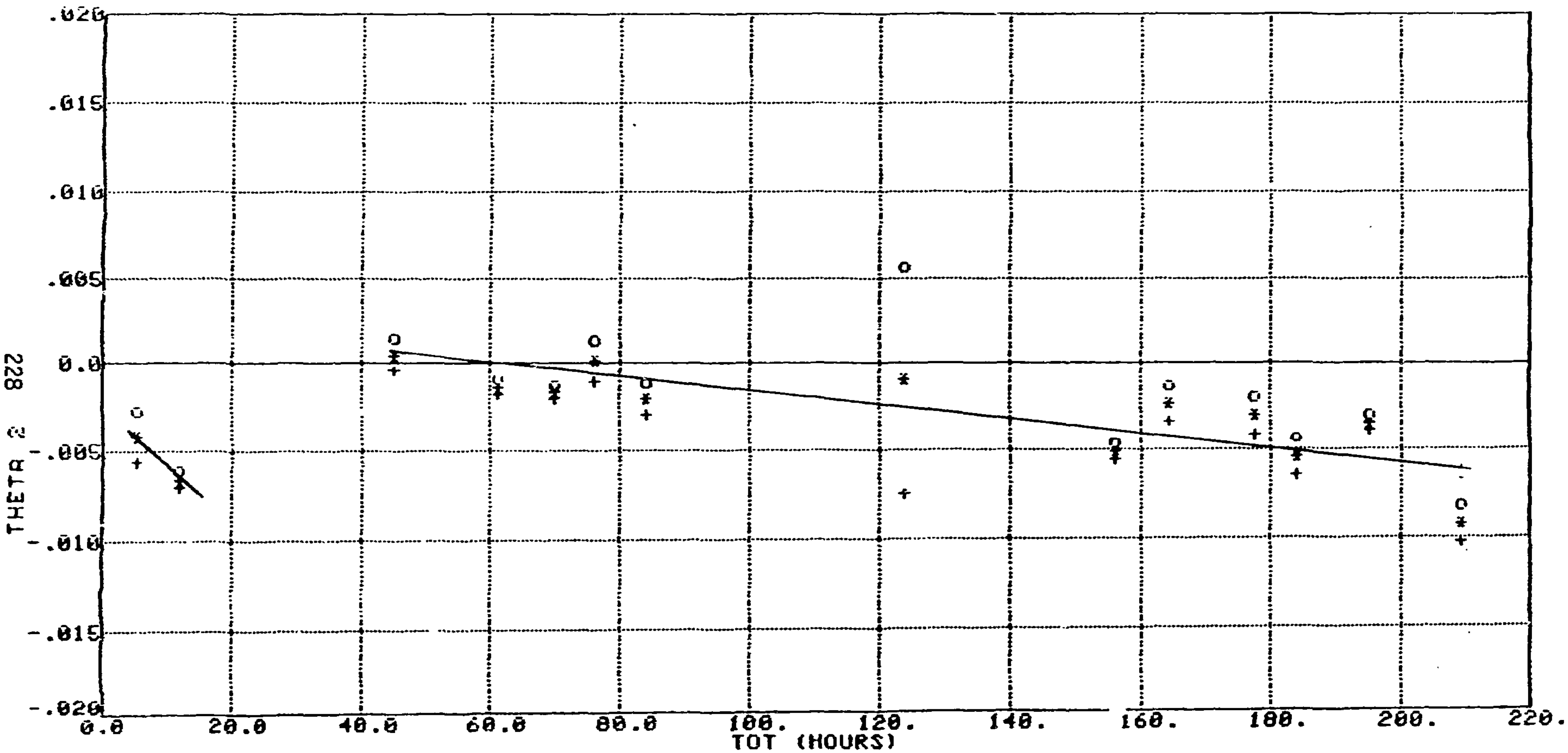

Figure 7.13 Compressor Rating For E1930 (Mode 2000)

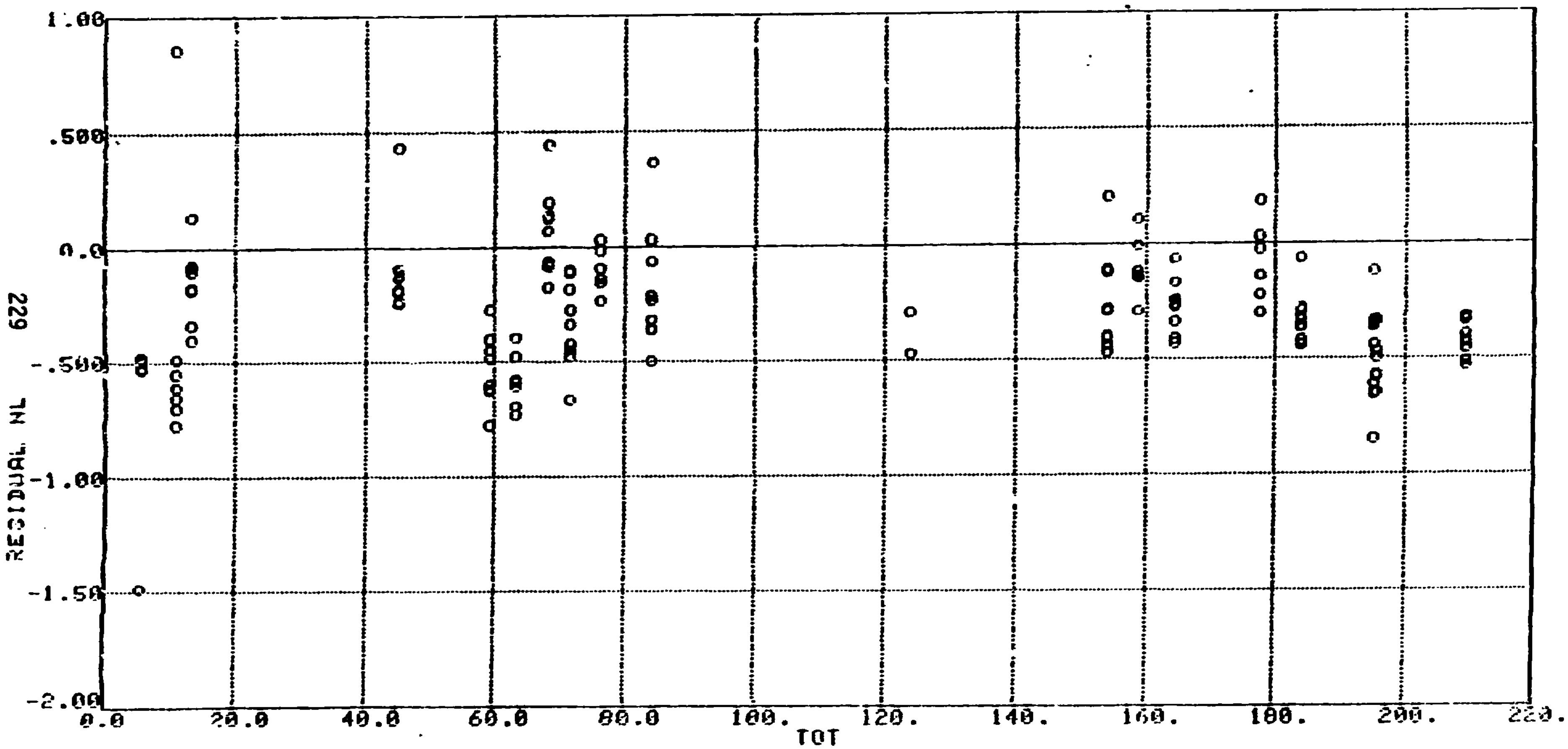

Figure 7.14 Residual NL for E1930

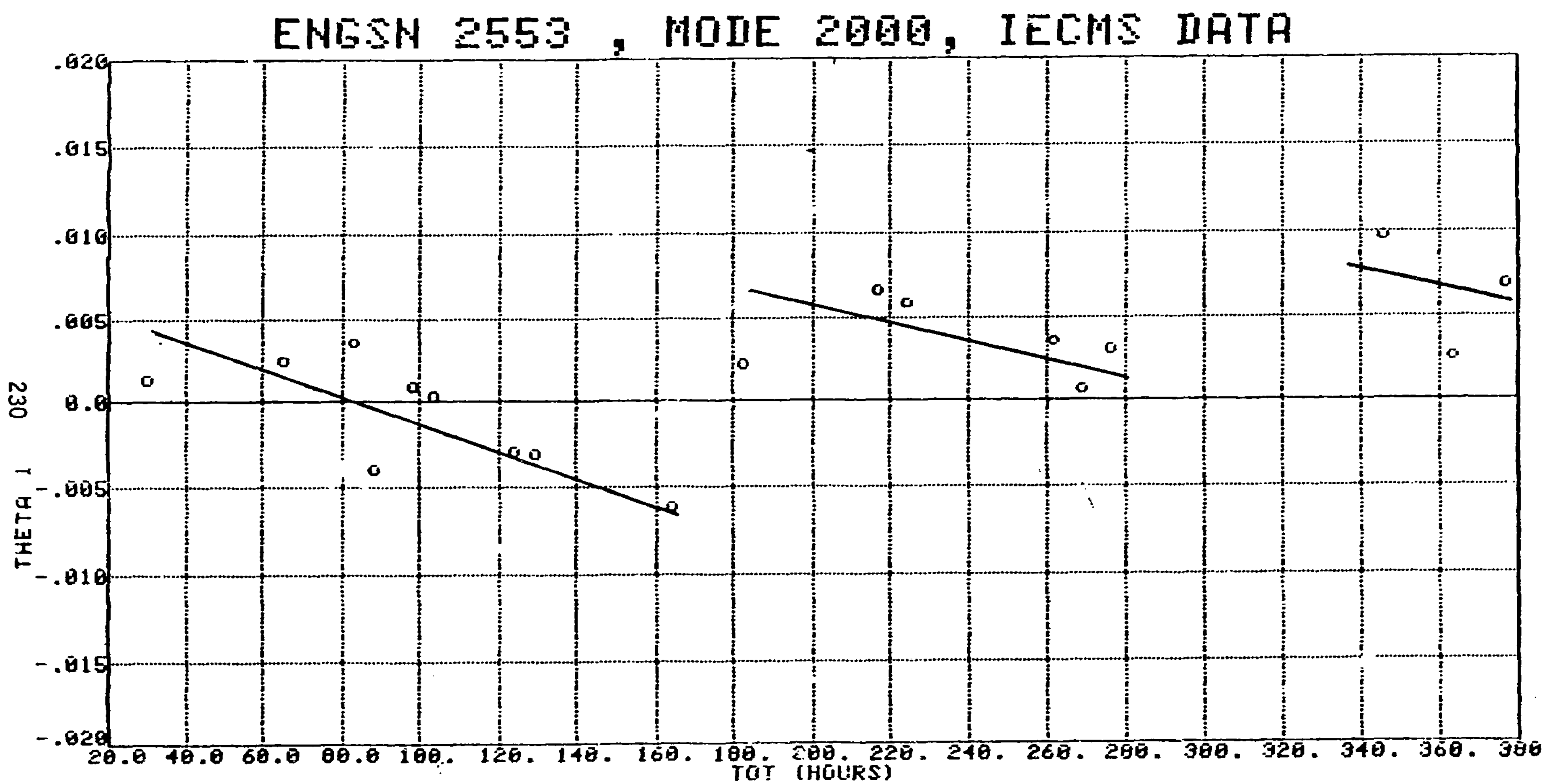

Figure 7.15 Low Spool Rating For E2553 (Mode 2000)

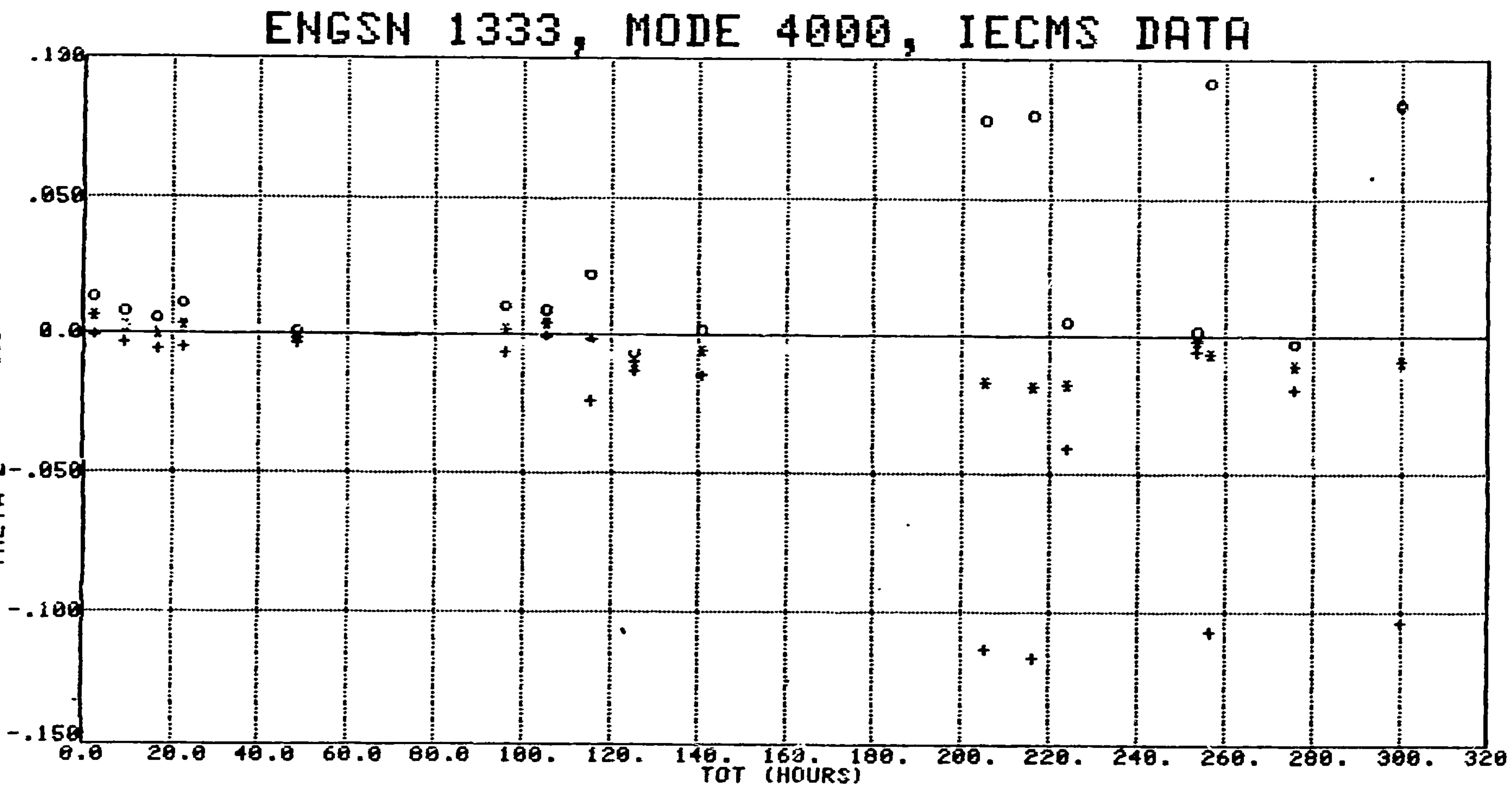

Figure 7.16 High Pass Turbine Rating - Cruise Mode Data

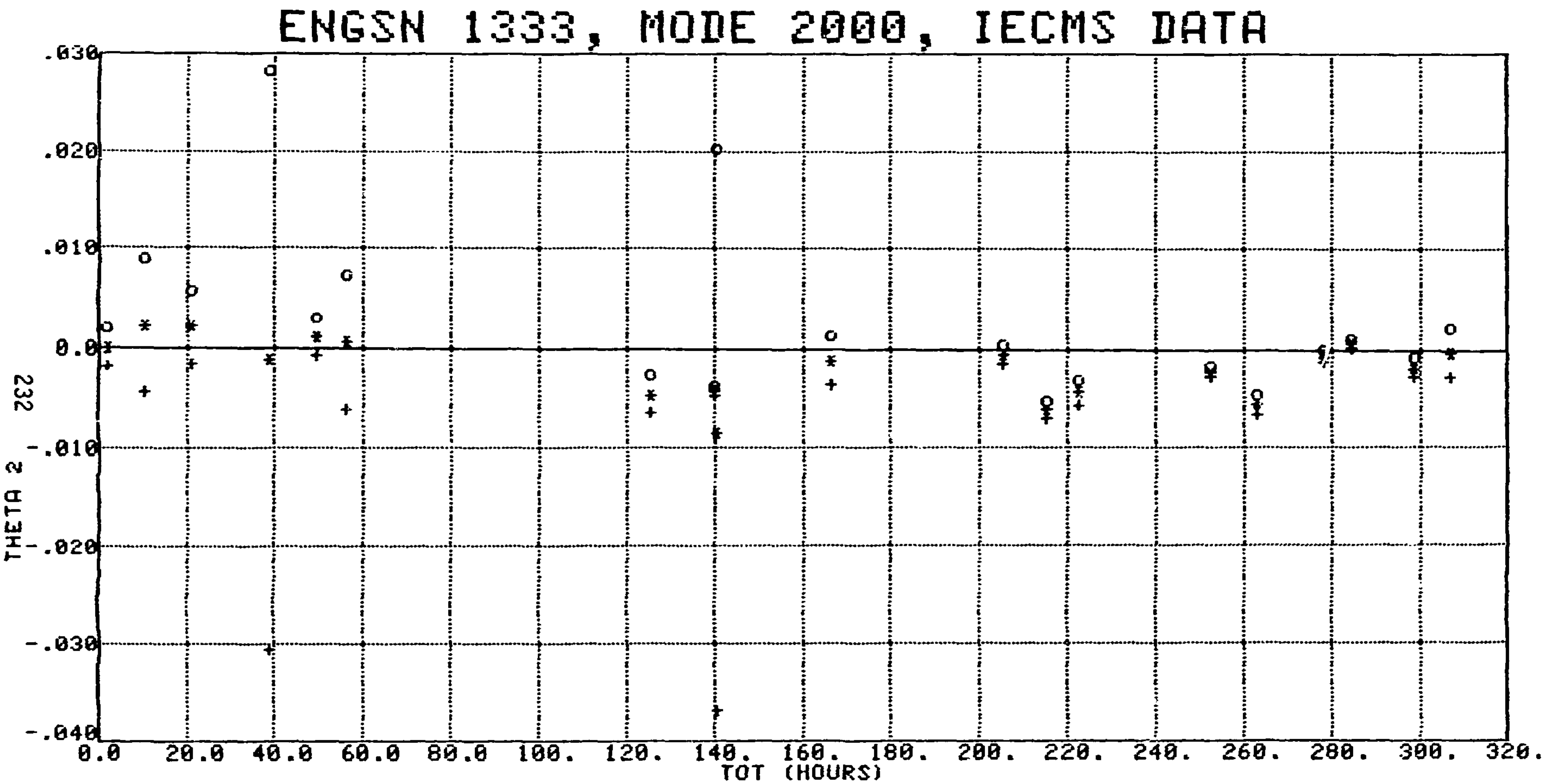

Figure 7.17 High Pass Turbine Rating - Takeoff Mode Data

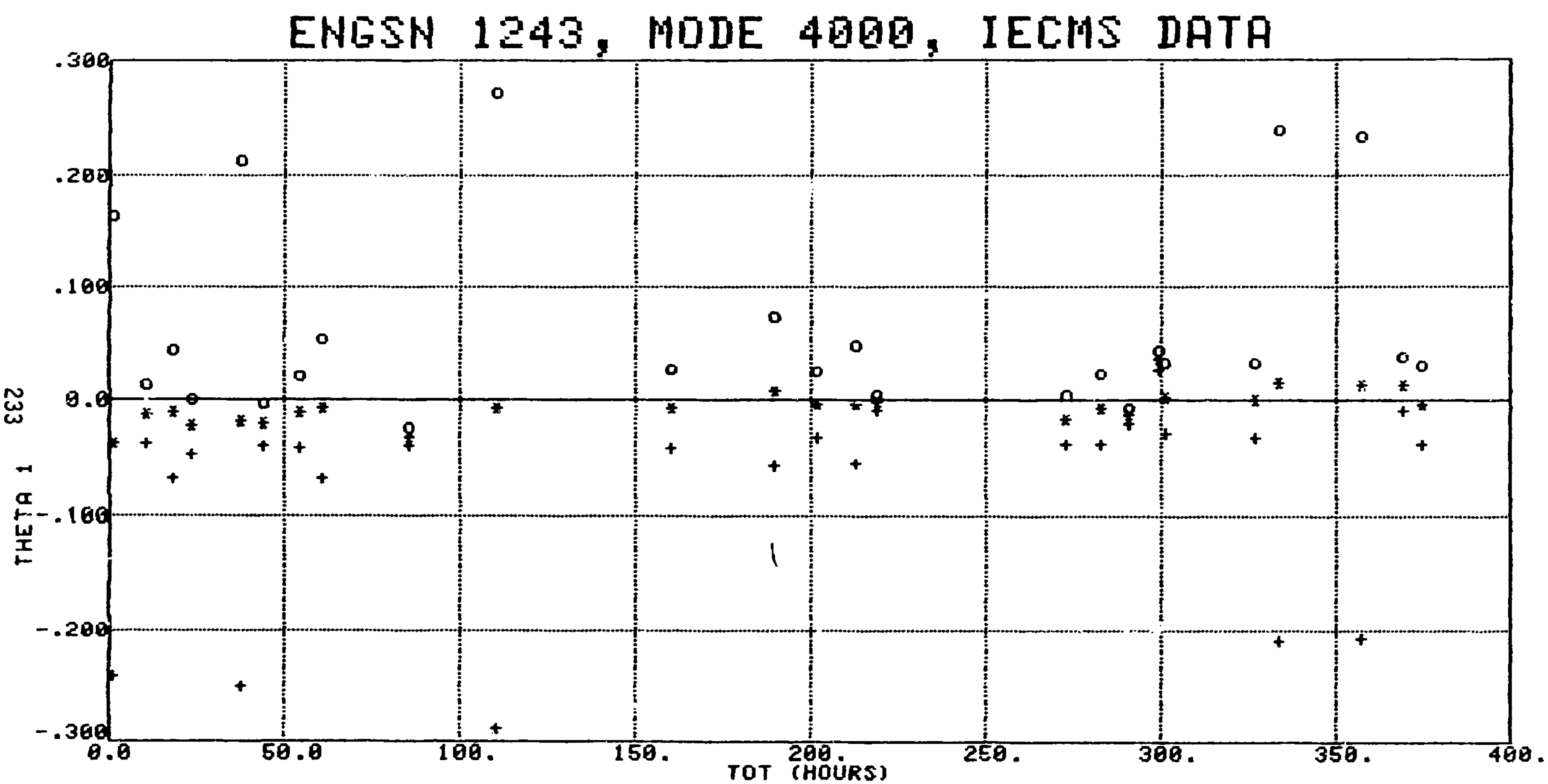

Figure 7.18 Low Spool Rating - Cruise Mode Data

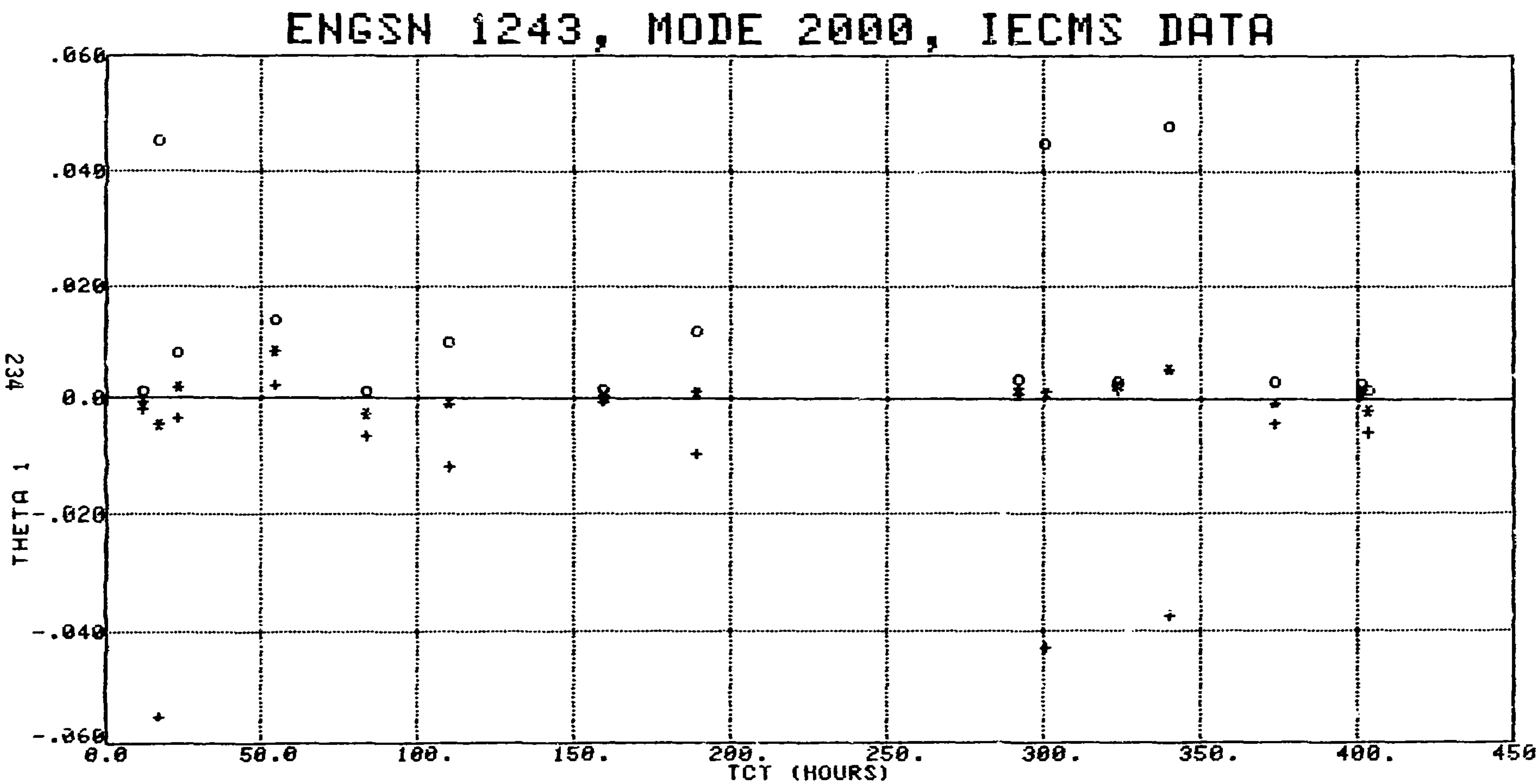

Figure 7.19 Low Spool Rating - Takeoff Mode Data

VIII. SUMMARY AND CONCLUSIONS

This report has addressed the problem of reducing engine monitoring data to usable performance parameters and integrating these data into the Air Force maintenance/logistics organization to support engine management. The engine performance monitoring problem was introduced in Chapter II and then a mathematical solution to the problem was presented in Chapter III. The method developed in Chapter III, the thermodynamic cycle monitoring algorithm, demonstrates that it is theoretically possible to derive quantitative health indices from engine monitoring data.

The thermodynamic cycle monitoring (TCM) algorithm is based on state of the art techniques in statistical regression analysis and nonlinear estimation theory. Included in this general methodology are completely new and extremely promising sensor validation and trending routines. The mathematical methods developed in Chapter III have been implemented as a set of flexible and efficient software modules. The results of the TCM algorithm as applied to TF34/TEMS, F100/EDS, and TF41/IECMS data bases are presented in Chapters V through VII, respectively. Results of Chapter V indicate that it is practically feasible to derive engine/module health indices from engine monitoring data and to correlate the results with engine maintenance actions. The successful detection and isolation of failed sensors is also demonstrated. The results in Chapters VI and VII are mixed, yet valuable insights are gained into the data collection requirements necessary for successful implementation of the TCM algorithm.

The requirements for integration of performance monitoring into the Air Force engine management process were presented in Chapter IV. Implicit in the requirements identified by this study is the general concept for a Maintenance Information Management System (MIMS). The MIMS is a vehicle for integrating performance diagnostics and automatically acquired data into existing information flow, and facilitating user access of summary and trend information. Data management architecture, information flow, and hardware/software integration aspects are the fundamental elements of the requirements definition.

Using the Phase I study results and methodology presented in Chapters II and III, SCT developed software to support the maintenance information management system. This included development of applications software, a specialized data manager, and graphics terminals/display drivers. The software architecture includes sequential acquisition/qualification of data, efficient user interface, multi-indexed query capability, and multimedia data transfer and output. In short, the MIMS links local data collection and processing for maintenance decisions with centralized historical data preservation and analysis for logistical decisions.

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